DEFINING AND MEASURING ENGAGEMENT WITH DIGITAL BEHAVIOR CHANGE INTERVENTIONS: APPLICATION TO THE SKATA MOBILE APPLICATION FOR FAMILY PLANNING IN INDONESIA

By
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Abstract

Background: There is growing excitement about the potential of digital behavior change interventions (DBCIs) in low and middle-income countries. However, there is limited research on how to define and measure factors that facilitate and inhibit continued participation or "engagement" in DBCIs.

Parent Study: The dissertation was situated in the *MyChoice* program*,* which addresses family planning (FP) demand, supply and service delivery issues. The *Skata* application (app) and website are a portion of the digital strategy for generating FP demand in Indonesia.

Methods & Results: This study begins with a concept explication of engagement with DBCIs. The concept consists of three dimensions (cognitive, emotional and behavioral engagement) and four phases describing behavioral engagement over time. An Extended Engagement Index (EEI) is proposed to align with the concept of engagement with DBCIs. Applying the EEI to Skata mobile application and website usage data, we find high internal consistency of the scale (Chronbach's Alpha = .8630) and good criterion validity in comparing EEI to a more traditional engagement measure, specifically length of DBCI use. Five factors representing motivations for Skata use are identified, four of which describe seeking and scanning motivations that significantly predict higher engagement with Skata. Comparing these motivations and experiences of Skata engagement qualitatively, we find scanners tend to access a broad variety of features while seekers making planning and contraceptive decisions tend to use a narrow set of features repeatedly before disengagement. For many Skata users, interpersonal communication represents an important step in the conceptual framework connecting engagement in a health topic with engagement in a related DBCI, and mediating the path to behavior change.

Significance: The field of digital health is growing rapidly, but standardized metrics have not been widely adopted and thus engagement with DBCIs is still understudied. This research fills significant gaps in the literature to develop a framework for DBCI outcome evaluation.

Thesis Committee Readers

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In addition, support for travel and lodging to conduct data collection were provided by the Johns Hopkins Center for Global Health's Global Health Established Field Placements program in 2015. Support for transcription and translation of interviews as well as purchase of qualitative data analysis software was supported by an award from the Center for Qualitative Studies in Health and Medicine in 2016. Additional support for research and dissemination activities was provided through two Health, Behavior and Society Distinguished Dissertation Research Awards in 2016 and 2017.

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Abbreviations

A/B testing: A method of comparing two versions of a webpage or app against each other to determine which one performs better

AIC: Akaike's information criterion. An estimator of the relative quality of statistical models for a given set of data. The lowest AIC among models is generally preferred.

ANOVA: Analysis of variance. A statistical procedure used to analyze the differences among group means.

App: Application, as in mobile application.

BIC: Bayesian information criterion. A criterion for model selection among a finite set of models. The lowest BIC among models is generally preferred.

BKKBN: Badan Kependudukan dan Keluarga Berencana Nasional. The national family planning office of Indonesia.

CCP: Johns Hopkins Center for Communication Programs

CMMC: Communication and Mass Media Complete. A database of research in areas related to communication and mass media.

CPR: Contraceptive Prevalence Rate

DBCI: Digital Behavior Change Intervention

DHS: Demographic and Health Survey

DIEGO: Digital Health Engagement Model proposed by O'Connor et al. 2016

EFA: Exploratory Factor Analysis

EI: Engagement Index proposed by Peterson and Carrabis 2008 and applied by Taki et al. 2017. Peterson and Carrabis 2008 index includes subscales for Click Depth (CD), Duration (D), Recency (R), Loyalty (L), Brand (B), Feedback (F), and Interaction (I). Taki et al. 2017 index includes subscales for Click Depth (CD), Recency (R), Loyalty (L), Feedback (F), and Interaction (I).

EEI: Extended Engagement Index proposed and partially applied in this dissertation (2018). Informed by the Peterson and Carrabis 2008 and Taki et al. 2017 Engagement Index. Includes subscales for Cognitive Engagement (CE), Click Depth (CD), Duration (D), Recency (R), Loyalty (L), Feedback (F), Interaction (I), Feature Breadth (FB), and Feature-Specific Use (FSU).

FP: Family planning

HCI: Human-Computer Interaction

ID: Identification number

IRB: Institutional Review Board

IUD: Intrauterine device

JHSPH: Johns Hopkins Bloomberg School of Public Health

LARC: Long-acting Reversible Contraceptive

LMIC: Low and Middle-Income Country

mCPR: Modern Contraceptive Prevalence Rate

mERA: mHealth Evidence Reporting and Assessment guidelines described by Agarwal et al. 2016

MeSH: Medical Subject Heading

mHealth: Mobile health

MLR: Multiple Linear Regression

MoTech: Mobile Technology for Community Health. An open source software package from the Grameen Foundation that allows receipt and delivery of information to mobile phones.

MTUAS: Media and Technology Usage and Attitudes Scale proposed and applied by Rosen at al 2013

MyChoice: Right Method. Right Time. MyChoice. Reinvigorating the Family Planning Program in 12 Selected Districts in Indonesia program. A three-year health communication project in

Indonesia, funded by the Bill and Melinda Gates Foundation and led by the Johns Hopkins Center for Communication Programs (JHUCCP).

PAM: Patient Activation Measure

SBCC: Social and Behavior Change Communication

Skata: A mobile application and website developed as part of the MyChoice program to generate increased demand for family planning, specifically for long-acting reversible contraceptives, and to assist couples in planning their fertility goals and selecting modern contraceptive methods that aligns with their fertility goals.

SMS: Short message service. Also referred to as text messages.

TTM: Transtheoretical model proposed by Prochaska & DiClemente, 1983. Also referred to as the Stages of Change model.

U&G: Uses and Gratifications theory proposed by Katz, Blumler and Gurevitch 1973.

VIF: Variance Inflation Factor

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Chapter 1: Introduction

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Background

While impact evaluations of digital health interventions for social and behavior change communication (SBCC) are now becoming more common, conclusions vary and little attention has been paid to how exposure to digital behavior change interventions (DBCIs) plays a role in behavioral outcomes. Exposure to DBCIs is often referred to as 'engagement,' signaling both a metric for use of the intervention as well as mental energy invested into exploring and interacting with intervention content, measured over some period of time. This novel term – engagement rather than exposure – underscores the fact that there are differences in the way we conceptualize and measure exposure to DBCIs as opposed to traditional communication platforms. Unlike exposure, engagement may include assessment of initiation of intervention use. Similar to exposure, engagement is largely focused, however, on the act of continuing to use an intervention over time. Metrics for engagement in digital health have been wide-ranging, reflecting a lack of consensus about what the concept fully entails and how indicators can best be developed to capture the phenomenon.

Although there is a limited literature evaluating the concept to date, engagement is a fundamental concept for digital health evaluation. Compared to traditional media interventions, digital behavior change interventions (DBCIs) uniquely place the audience in control of their exposure to messaging. The audience is in charge of the intervention medium (e.g., computer, mobile phone, tablet, etc.), and these communication channels are uniquely integrated into peoples' daily lives – sometimes resting in the palms of their hands. As a result, DBCI audiences take an active role in creating the communication experience. In this active media consumption model, a major challenge to changing behavior is users' common and substantial drop-off in using these interventions (Wanner et al. 2010). If participants are inadequately engaged with a DBCI, the intervention cannot lead to psychosocial changes that predict behavior change, and the intervention fails to act as the program intends – having little impact on behavior and subsequent health outcomes. With substantial financial and human resource investment being directed towards DBCI development, particularly for public health programs in low and middle-income countries, it is imperative that we understand the factors that facilitate DBCI success in affecting behavior change. Engagement is at the heart of factors that ensure DBCI success.

To date the literature has been insufficient in understanding how engagement plays a role in DBCI evaluation models. The concept of engagement in digital health lacks consistency in its definition and operationalization; it is most often measured through active interaction with the program (i.e., number of visits, length of visits, number of pages viewed, number of message responses, etc). There has been little uptake of a robust and comprehensive summary measure for engagement that could be comparable across DBCIs.

Engagement data is procured either through self-report or use of data exhaust. Data exhaust is the data produced as a byproduct of intervention use. These data are rich, unobtrusively collected in real-time and can provide valuable insights into engagement. However, data exhaust may not fully describe the way in which interaction with DBCIs results in further communication and engagement with the health topic (i.e., skills practiced as a result of interacting with content, discussion of content with others).

Study rationale

This study was conducted to fill several critical gaps in the digital health literature. Addressing the heterogeneity of definitions and measures for engagement, this dissertation uses concept explication to clearly articulate the concept of interest and propose a robust index that can be used to assess all aspects of engagement with DBCIs. The study then applies this measure to assess its reliability and validity in DBCI research, and to identify individual-level predictors of engagement within the context of the Skata mobile application and website in Indonesia.

Finally, the research challenges DBCI evaluation models connecting engagement with behavior change by exploring the engagement experiences of Skata users.

Study context

This dissertation research takes place within the context of the *Right Method. Right Time. MyChoice. Reinvigorating Family Planning in Indonesia* (MyChoice) program. MyChoice is a three-year health communication project in Indonesia, funded by the Bill and Melinda Gates Foundation and led by the Johns Hopkins Center for Communication Programs (JHUCCP) (Institutional Proposal Number 15043035). The program aims to promote family planning (FP) uptake and appropriate method choice, matching users' fertility goals and life stage.

Indonesia's national government demonstrated its commitment to family planning through participation at the 2012 London Summit on Family Planning and a significant budget allocation of $180 million/year to support family planning programs in the country. Indonesia's family planning board, BKKBN, has supported the *MyChoice* project by contributing funding and involving its leadership team at national, provincial and district levels in program design and implementation. BKKBN has taken successful JHUCCP interventions to scale in the past, and JHUCCP intends for BKKBN to take ownership of successful elements of the MyChoice program as well.

Despite Indonesia's long history of national support for FP, the modern contraceptive prevalence rate (mCPR) has been stalled at around 60 percent for over a decade, since 2003, and was recorded at 57.2% in 2017 (DHS Indonesia 2017). Furthermore, the FP method-mix has shifted towards heavy use of short-term methods such as injectables and oral contraceptives over the last 20 years, with 32% and 14% of married FP-using women ages 15-49 using injectables and oral contraceptives in 2012 compared to 12% and 15%, respectively in 1991 (DHS Indonesia 2012). These methods are popular and effective in the short term, but more difficult to use consistently and therefore less reliable for longer spacing of births or after a couple has achieved their desired family size. Long-acting reversible contraceptives (LARCs), such as intra-uterine devices (IUDs) and implants, are more reliable for long-term spacing and limiting of births, but use has fallen from 13% and 3%, respectively in 1991 to 4% and 3% in 2012 (DHS Indonesia 2012).

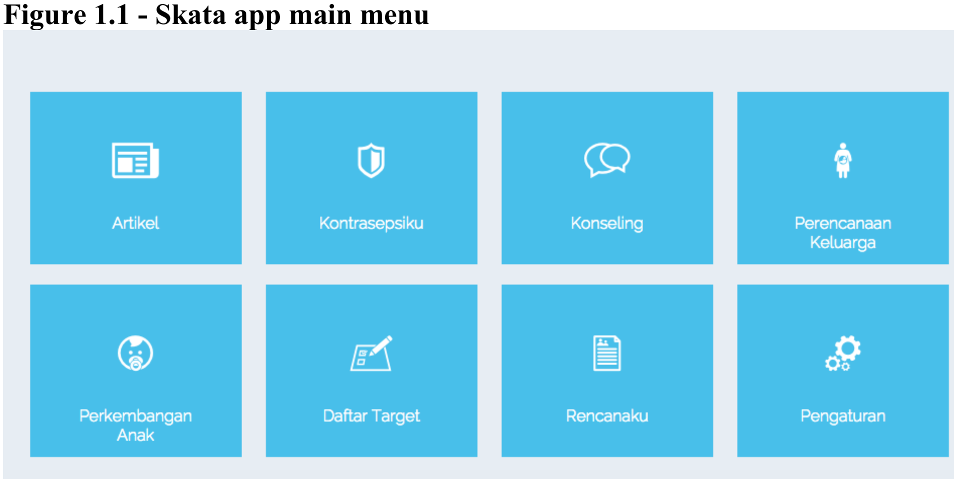
The *MyChoice* program includes supply side and demand generation communication programs to promote underutilized LARCs for women whose life stage calls for greater control over long-term spacing and limiting of births. The program also has a family planning service delivery component to support health workers in counseling and providing LARCs to their patients. JHUCCP, as one part of their efforts towards FP demand generation, designed a mobile application and mirrored website entitled Skata. JHUCCP worked with the Jakarta-based digital production agency MobileForce to develop the Skata DBCI. Skata was intended to be a lifestyle intervention to help women and their partners plan for major life events related to making a family, such as planning for marriage and children. *Skata* is a contraction meaning "together – one" in the language Bahasa Indonesia. It connotes that together couples can identify one plan for their family, including a FP method that is right for their life stage.

Skata was developed over the course of one year and launched nationwide in April 2016. A screen capture of Skata's main menu is shown below (see Figure 1.1). Skata content falls under the broad categories listed, with descriptions of content in the category noted:

- <u>Articles</u>: Articles about FP and FP methods
- <u>Contraception</u>: Information about FP methods including facts, advantages, drawbacks and recommendations for appropriate use and a quiz to find out the best FP method for you; Contraceptive myths and facts quiz; Contraceptive reminder feature; Menstrual period tracking feature
- <u>Counseling</u>: A frequently asked question bank on FP-related issues; A GPS-enabled feature to search for the nearest healthcare provider

- Family planning: Child education financial planning checklist; School calendar; Immunization calendar
- Child milestones: Information about developmental milestones for children from newborn age through five years old
- Checklists: General and daily to-do checklists
- My Plan: Life simulation feature to plan timing and spacing of marriage and child bearing. After a series of questions, produces a timeline of the user's life plan as a couple, up to approximately age 70.
- Settings: Login and registration profile information, notification settings and the ability to make changes to profile and settings

Figure 1.1 - Skata app main menu



Research aims

1. **Research Aim 1:** Understand how "engagement" is conceptualized in digital health literature and related fields to outline a comprehensive set of indicators that can be used to operationalize engagement within the context of DBCIs.
    a. Objective 1: Demonstrate the diversity of definitions of engagement that exist in the literature

   b. Objective 2: Identify commonalities in the definitions to propose a descriptive definition of engagement with a specific focus on engagement with DBCIs
   c. Objective 3: Identify an appropriate suite of indicators to use to robustly measure the clarified engagement concept
2. Research Aim 2: Apply the operationalized engagement measure to identify factors correlated with engagement in the Skata mobile app, including motivational factors that may drive engagement.
   a. Objective 1: Apply the suite of indicators proposed in Research Aim 1 to assess engagement with the Skata mobile app/website
   b. Objective 2: Validate the engagement measure, comparing it to a more traditional measure of engagement
   c. Objective 3: Identify patterns underlying use of the Skata app/website
   d. Objective 4: Establish a relationship between Skata engagement and individual-level factors that characterize app/website users
3. Research Aim 3: Understand the Skata user's engagement experience, including how motivations for use frame the engagement experience and may lead to mechanisms for changing planning and contraceptive decision-making behaviors.
   a. Objective 1: Explore how motivations for Skata use shape users' patterns of app feature use over a one-month period
   b. Objective 2: Understand the process by which engagement with Skata may lead to behavior changes in planning one's family and using contraception

Conceptual model

The conceptual model for this dissertation research is presented in Figure 1.2. This framework simplifies and adapts a framework from Perski et al. 2016 that conceptualizes the influences that affect engagement with DBCIs. My conceptual framework extends the Perski et al. 2016 model by stitching it to a model by Bull and Ezeanochie 2016, which offered an integrated theory of mHealth.

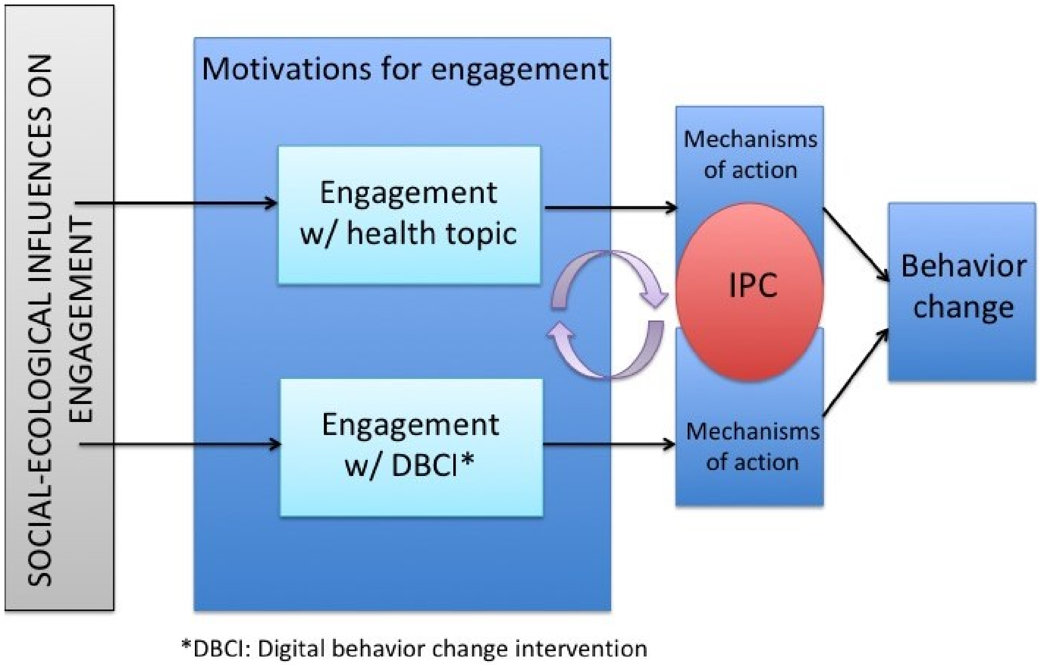
The conceptual model presented here depicts a range of social and ecological factors that influence engagement – both with a health topic as well as DBCIs related to the topic. Some influences may only be relevant to DBCI engagement (e.g., individual-level comfort with technology, national technology infrastructure), so these influences are depicted with separate arrows each connecting to engagement.

One individual factor of particular salience for engagement is an individual's motivation for engaging. Some users may be motivated to engagement with the health topic and related DBCIs to scan and learn broadly about the topic, while others may be motivated to seek information with an intention to change their behavior.

As presented in the model by Bull and Ezeanochie 2016, engagement with the topic and related DBCIs each can lead to mechanisms of action that are described by classic social and behavior change and health communication theories. These may include changes to constructs such as knowledge, attitudes, normative perceptions, cues to action, self-efficacy, interpersonal communication and others. Incorporating the concept of reciprocal determinism from Social Cognitive Theory, interpersonal communication, in particular, is depicted as a bridging mechanism of action between engagement with the health topic and engagement with related DBCIs. The cyclical arrows in the model represent this reciprocal relationship. Finally, through mechanisms of action we expect to see some behavior change.

While my initial manuscript explores engagement with DBCIs generically, my later manuscripts are contextualized to Indonesia and focus on changes in family planning and contraceptive method decision-making resulting from engagement with the Skata mobile application and website, and broadly with FP as a health topic.

Figure 1.2 - Conceptual model



Dissertation organization

This dissertation is organized into six chapters.

Chapter 1: Introduction

This chapter provides an overview on the importance of engagement as a mechanism through which success of DBCIs can vary in achieving behavior change. It also includes the aims for this dissertation, and the conceptual model.

Chapter 2: Literature Review

This chapter synthesizes the literature review on engagement with digital programs, offering a framework for the social and ecological factors that influence engagement with DBCIs. While some influences are similar to the demographic, psychographic, interpersonal and behavioral factors that influence engagement in health topics in general, other influences are more specific to the digital realm – such as app or website architecture and usability factors, and the technology infrastructure undergirding the DBCI.

Chapter 3: A concept explication to define and measure engagement with digital behavior change interventions

This chapter is a concept explication that examines the concept of engagement with digital behavior change interventions. It proposes a comprehensive definition for engagement with DBCIs, as well as a framework for operationalizing the concept so that it can be comparable across interventions.

Chapter 4: Predictors of engagement with the Skata mobile application for family planning in Indonesia: Application of the Extended Engagement Index

This chapter presents a validation study of the Extended Engagement Index (EEI). The EEI offers a more robust measure of engagement than traditional measures, such as length of DBCI use. The EEI is also used as an outcome measure, allowing regression analyses to identify individual-level demographic, app access and motivational predictors of engagement.

Chapter 5: The role of motivation in shaping experiences of engagement: Exploration of use of the Skata mobile application for family planning in Indonesia

This chapter presents the findings of a qualitative exploration of Skata engagement experiences, stratified by motivations to use the DBCI. Differences in patterns of feature use are discussed, and the role of interpersonal communication is explored as a mediator between engagement with Skata and engagement with FP in general, as well as between engagement with Skata and adoption of a contraceptive method.

Chapter 6: Discussion

The sixth chapter provides a summary of findings and overarching conclusions from the three studies in this dissertation. The chapter also discusses the strengths of this dissertation as a DrPH thesis, limitations of the study and implications for public health and digital intervention practice.

Appendices

There are 12 appendices in this dissertation.

- Appendix 1 provides the Octalysis framework (Chou 2016), a framework for engagement in the context of electronic gaming.
- Appendix 2 provides the search terms used to collect the data used for the concept explication.
- Appendices 3-6 provide supplemental material to the EEI validation study. These appendices include the Skata app and website architecture, a dictionary describing the pages of Skata, shell data tables describing the data framework, and the formulas used to calculate the EEI for Skata.
- Appendices 7-9 provide supplemental material to the qualitative exploration of Skata engagement. These appendices include the interview consent form and interview guides for the usability test and follow-up interview rounds of data collection.
- Appendices 10-11 provide supplemental material to the discussion chapter of this dissertation. They include a table of Skata's digital assets as of March 2018, and images of the versions of Skata tested in December 2015 - April 2016 as well as a revised version of Skata from March 2018.
- Appendix 12 provides a list of venues where preliminary findings from this dissertation have been disseminated.

Following the appendix there is a bibliography and the author's curriculum vitae.

Institutional Review

This dissertation research was conducted with approval from the Johns Hopkins Bloomberg School of Public Health Institutional Review Board (JHSPH IRB) under the study title "MyChoice: Reinvigorating the Family Planning Program in Indonesia" (IRB number: 00006181). In addition, the study was reviewed and approved by the IRB at the University of Indonesia School of Public Health (IRB number: IORG0005102, DUNS 726877181).

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Chapter 2: Literature Review – Conceptual foundations of engagement, Influences on Engagement

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Chapter 2: Literature Review

Engagement is a fundamental concept for digital health evaluation, however, there is a limited literature evaluating the concept to date. The concept of engagement with digital behavior change interventions (DBCIs) lacks consistency in its definition and operationalization. This chapter reviews the literature on engagement within digital health to differentiate what constitutes the phenomenon versus that factors influence engagement.

Conceptual foundations of engagement

The concept of engagement was explored in several disciplines prior to being used in digital health interventions for behavior change. Brodie et al. 2011 reviewed the history of customer engagement, which became a more commonly used term in marketing literature starting in 2005. Brodie et al. noted that, since 2005, 'engagement' has replaced terms such as involvement and participation. Although the term engagement traces back to the 17th century, when it was used to describe obligation and ties of duty, it has evolved in the marketing literature to describe a voluntary state of being, as well as short- and long-term processes that develop over time.

In recent decades the term 'engagement' has been taken up by fields ranging from psychology to sociology, political science, organizational behavior and marketing, "leading to a variety of conceptual approaches that highlight different aspects of the concept," including its cognitive, emotional and behavioral dimensions (Brodie et al. 2011). Citing organizational behavior research by Patterson, Yu and de Ruyter (2006), cognitive engagement was defined as the level of concentration focused on an organization, or absorption by the organization. Emotional engagement was described as the individual's sense of belonging to the organization, or dedication to the organization. Finally, behavioral engagement was defined as the level of energy spent and interaction that takes place between the individual and organization. While organizational engagement describes engagement with an institution, customer engagement focuses on engagement with a product. Although the object of engagement varies, the facets of engagement described in each are similar. Specifically, the facets of engagement represent actions taken by the individual as well as changes taking place within the individual's psyche. As we apply these concepts to DBCIs, we may consider both germane, given that DBCIs are at once a product as well as a representation of health communities – an institution which one can belong to when considering a health topic.

Gaming literature has also focused on the concept of engagement. Octalysis is a gamification framework that explores how games can motivate players to continue to engage (See Appendix 1). The Octalysis framework posits that there are eight core drivers of human behavior that push a player to continue to play games: the desire for epic meaning and calling, development and accomplishment, empowerment of creativity and feedback, ownership and possession, social influence and relatedness, scarcity and impatience, unpredictability and curiosity, and loss and avoidance (Chou 2016). These drivers motivate a player to start playing, return to playing and dedicate time towards playing in order to make progress, express creativity and build up their status. Some of the drivers are considered motivations that relate to a player's right brain, associated with logic, calculations and ownership, while other drivers are more associated with the left brain, tapping into a player's creativity, expression and sociability. *Entertainment* or a need for escape, however, is the fundamental motivation driving game use. Therefore, the Octalysis framework helps us understand how to make a game engaging for the purpose of entertainment.

DBCIs, typically, assist individuals in making a specific health decision; therefore, *utility* may be a more salient driver of use. A study exploring use of gamification in a smoking cessation application found that there were three elements necessary to engender game engagement: an explicit purpose that the user recognized for the gamified app, alignment of game and user objectives, and good functionality allowing ease of use (El-Hilly et al. 2016). The first of these elements – known purpose – speaks to the importance of perceived utility in sustaining user interest in health-related gamified apps, and is markedly different from the expectations users have of digital games in general. While engagement in gaming literature is important to consider for understanding influences that can affect engagement with DBCIs that include gamified health content, we must consider how affect-based influences link to perceptions of the utility of content in DBCIs.

Patient engagement is the most proximate public health correlate to engagement with DBCIs, considering DBCIs facilitate informed consumers of healthcare and support shared decision making between patients and providers. Patient engagement is a ubiquitous term in public health literature. However, it is also inconsistently defined. Gallivan et al. 2012 described patient engagement as dynamic, interactive and iterative processes where the individual played an active and meaningful role in planning and decision-making for health services and policies that would affect their lives. Similar to Brodie et al.'s dimensions of customer engagement, Barello et al. 2016 discussed cognitive, emotional and behavioral components of patient engagement. The cognitive dimension of patient engagement is about a change in what the patient thinks and knows and how (s)he makes sense of the disease. The emotional dimension is connected to what the patient feels about the disease and his/her life condition linked to it. The behavioral dimension is about what patients do to face the disease condition. All put together, changes across these dimensions mark the level to which a patient is engaged in being active and effective managers of their healthcare (Barello et al. 2016).

Similar to the Octalysis Framework, some patient engagement literature on digital interventions focuses on the intervention's qualities that engender engagement. For example, Singh et al. 2016 provided a definition and framework for patient engagement within the context of digital health, focusing on the intervention's ability to enable collaboration between providers and patients, increase patient activation and participation in health decision-making, and facilitate information-sharing. The framework (Figure 2.1) indicated how features of a digital health intervention might satisfy first basic information-gathering and reminder needs for patients, and grow increasingly more complex as patients engage more deeply with health care and become more 'activated' to seek support for needs such as health tracking, relationship building, and entertainment or gamified behavior change. Where the Octalysis framework concentrated on factors that make a game engaging, Singh et el.'s framework outlines strategies for making a mobile health app engaging.

Both the Octalysis framework and the Singh et al. 2016 framework present *ways* to make a product engaging, however, the Mobile Application Rating Scale (MARS) includes a subscale to measure the *extent to which* an app is engaging. Rather than measuring a phenomenon taking place between a product and user, the MARS subscale focuses on attributes of the application alone. Specifically, the MARS engagement subscale requires researchers to rate the *possibility for interaction* that the application affords users (Bardus et al. 2016, Wilson et al. 2016, Schoeppe et al. 2017). Researchers assess whether the application is entertaining, interesting, allows customization, is interactive, and is well matched to its target audience. All five subscale items are scored on a 5-point likert scale, and the mean score is used as a measure of how engaging the app is considered to be. Compared to customer and patient engagement frameworks, the MARS engagement subscale does not validate its measure of engagement through feedback from users, remaining focused solely on qualities of the app from the perspective of researchers.

These foundations of the concept of engagement reflect a complex phenomenon in which there are multiple markers to consider in assessing whether a person is engaged, the intervention is engaging, and a process of engagement is developing over time. These precursor terms for engagement in DBCIs describe an iterative, interactive process through which the user's iterative interaction with the intervention can shape his or her communication experience. Dependent on the DBCI architecture, users may be able to select which messages to receive, in which order, and for how long. The architecture of a DBCI refers to the way in which the information is organized within the intervention. One of the most user-driven architectures is a matrix design, in which information is organized in an open menu allowing users to explore content without any programmatic constraints (Danaher et al. 2015). Operating under the assumption of matrix design architectures, a user has great control over their content selection behaviors. The content that users select and absorb can affect changes in their cognitive and emotional connection with the intervention and health topic – reflecting mechanisms of action that precede behavior change.

Related measures to engagement

Patient activation is a measure of psychosocial change that is often discussed interchangeably with engagement. Hibbard and Greene discussed the differences between the terms 'patient engagement' and 'patient activation,' noting that patient engagement includes the concept of activation (2013). Patient activation is based on the finding that being an engaged and active participant in one's own health care is linked to better health outcomes. It measures patients' ability to 1) self-manage symptoms, 2) engage in activity that maintains health function and delays decline, 3) be involved in treatment and diagnostic choices, 4) collaborate with providers, 5) select providers based on performance and quality, and 6) navigate the healthcare system. The Patient Activation Measure (PAM) assesses a patient's location in a process from believing the patient role is important, to having confidence and knowledge necessary to take action, to taking action to maintain and improve one's health, to staying the course even under stress (Hibbard et al. 2004). Patient activation is often measured by self-report, with the patient as the unit of analysis, comparing pre- to post-intervention use. In comparison, patient engagement focuses on engagement in care. In this thesis we focus on engagement in a different way than these concepts – the author focuses on engagement with DBCIs as an interaction between the patient and intervention. Rather than engagement in the health topic or in care decisions, engagement with DBCIs is concerned with intervention use.

Patient activation may logically follow from engagement with DBCIs as a mechanism of action affecting behavior change. By increasing use of and engagement with a DBCI, we assume there is a greater likelihood that mechanisms of action such as psychosocial changes will occur.

Psychosocial changes may include patients having greater willingness and sense of self-efficacy to take actions to manage their health and care, which PAM may detect. To date, studies have not directly assessed the relationship between engagement with DBCIs and subsequent changes in patient activation.

This thesis will focus on engagement with DBCIs, and build a link between engagement and mechanisms of action such as activation that predict behavior change. The study will focus on the context of family planning in Indonesia. In order to build linkages between engagement and mechanisms of action I will elaborate upon the concept of engagement with digital interventions and explore how use of specific features within a DBCI may reflect motivations for use. Motivations can be considered akin to communication needs or gratifications sought, as described in Uses and Gratifications (U&G) literature. According to U&G theory (Katz, Blumler, Gurevitch 1973), users actively consume media to gratify communication needs. In consuming media, users are gathering information to satisfy needs for factual knowledge, social knowledge —either reinforcement of one's attitudes, deeper personal insight, or correlational information— and to seek diversion. By outlining the connection between motivations, engagement and mechanisms of action leading to behavior change, this thesis validates a measurement model for DBCI effects on behavior change, as was described in the Conceptual Framework section of the introduction chapter of this dissertation.

Phases of engagement

There are several frameworks in the literature that elaborate on the concept of engagement by breaking engagement into phases. These models are a useful launching point for exploring how the concept has been defined and conceptualized in the literature, prior to reviewing the ways in which the concept has been measured.

Time is a critical element to the concept of engagement. O'Brien and Toms broke the multi-faceted experience of engagement into four stages: 1) the point of engagement, 2) a period of sustained engagement, 3) disengagement, and 4) re-engagement (2008). At each stage one can describe attributes of the users who are involved with the technology, the technology system, and the interactions between the user and system. Therefore, influences on engagement may vary depending on what stage of engagement a user is in. The factors that influence point of engagement, or whether a user decides to engage with a DBCI may be less salient once a user's engagement is sustained during the period of engagement.

Similarly, Ziebland et al. discussed phases to the engagement process, from gating to the engagement loop, resulting in a range of short- and long-term outcomes (2016) (Figure 2.2). Gating may precede O'Brien and Toms' point of engagement stage – it is the process where users assess whether they trust the site. Influences on gating may relate to an individual's trust in the health information provider. Ziebland et al.'s engagement loop further details the user experience during O'Brien and Toms' point of engagement and period of engagement stages. During the engagement loop users look for and evaluate the support provided, assessing its personal relevance. Specifically, users may try to understand 1) *who* the content is coming from and determine whether that is a relatable or credible source, 2) *what* information is being given to evaluate whether it is a match for their needs. These two steps of the engagement loop may overlap with O'Brien and Toms' point of engagement phase and suggest that the salience of the health issue in addition to individual factors such as trust in spokespeople influence engagement. Next, Ziebland et al. posit that participants 3) *compare* the information on the site to their own experiences, and finally some 4) *share* their own experiences. These two steps help explain what users may be doing during the period of engagement phase and indicate that salience of the health topic as well as app factors such as inclusion of sharing features may influence engagement. Comparing content helps users determine if the material is suitable and relevant, and sharing offers an opportunity for interaction with others. By sharing experiences, participants may affect subsequent users' evaluation of who is offering content and what is being said – affecting the point of engagement for future users. This describes a social factor that seems to influence others' engagement with DBCIs. Finally, Ziebland notes that the third phase of the engagement process with patient experience websites is user reflection and evaluation of the benefits of their use of the site. Benefits of engagement may include finding information, feeling supported, maintaining relationships with others, affecting behavior and other outcomes. These evaluations suggest that users reflect on whether the gratifications they sought were ultimately fulfilled through their engagement with the intervention.

It is important to note that Ziebland et al.'s model focused specifically on online patient experience websites, where there may be no ultimate goal of changing a health outcome. Patients typically use experience forums to gain coping skills to deal with a health outcome or diagnosis. Comparatively, DBCIs usually focus on changing behavior with the goal of preventing some negative health outcome. So, although the Ziebland et al. framework for engagement is useful for helping us to consider the changing weight of influences on engagement over time, it lacks an end point to the measurement model for engagement critical to evaluation of DBCI programs.

Influences on engagement

Several additional frameworks in the literature explicitly elaborate on the factors that influence engagement with digital health interventions and DBCIs in particular. These models outline important contextual factors that affect engagement. The models are presented in sequence, from ones with a narrow set of primarily individual factors influencing engagement to models that gradually incorporate more social and national-level factors. While my dissertation does not explore all of these influential factors, understanding the wider landscape is helpful for pinpointing how my research relates to other studies of DBCIs.

O'Connor et al. developed the DIgital Health EnGagement MOdel (DIEGO) in which engagement is defined as the process by which an intervention team makes individuals aware of an intervention (e.g. marketing techniques) (2016). DIEGO focuses on the first stage of engagement – enrollment in digital health interventions. This could overlap with O'Brien and

Toms' point of engagement phase as well as the Ziebland's gating stage of engagement. The DIEGO conceptual model (Figure 2.3), however, builds upon those models by including many psychosocial factors that the authors suggest are important at the outset of intervention use, and may sustain engagement. The DIEGO model includes four major components: 1) making sense of the intervention (patient's personal agency to use intervention, awareness/understanding of the intervention, motivation to use intervention), 2) public perception of intervention quality (quality of intervention, quality of information, usability), 3) public support for enrolling in intervention (clinical endorsement, personal advice or recommendations from family/friends, direct support from offline family/friends, enrollment strategy to promote enrollment through marketing), and 4) patient experience actually registering for the intervention (security and privacy concerns, digital literacy skills and appropriate equipment, personal lifestyle accommodating use of digital intervention) (O'Connor et al. 2016). This model highlights the way in which the user's characteristics, their social environment, and the intervention's characteristics all play important roles over time, from initiation of engagement (gaining support for enrolling) through the period of engagement (making sense of the intervention).

Bennett et al. 2017 complements the DIEGO model by discussing the influence of health locus of control on use of health applications. While DIEGO noted that part of the process of making sense of the intervention is the individual-level factor of feeling *motivated* to understand and improve one's health, Bennett points to the importance that individuals have to believe they *have control* over their own health. This belief, a stronger initial health locus of control, predicts how much patients are *willing to use* health applications and online trackers. While Bennett et al.'s study focused on the point of engagement stage, it is possible that health locus of control would also influence the length of the period of engagement with a digital health intervention.

The Ritterband et al. 2009 behavior change model for Internet-based health interventions moves beyond the point of engagement, considering the mechanisms at work when an individual uses a digital intervention that intends to change behaviors. Thus, it focuses on stages from point of engagement through a period of sustained engagement to identify the processes of change that may occur in this time period. While the authors did not use the term ‘engagement’ in their study, the model is relevant because it focuses on website use leading to health behavior change. Ritterband et al. noted that their conceptual model pulls from theories of motivation, psychological models, social marketing and advertising, Web and information architecture design, and behavior change theory. The model (Figure 2.4) shows that website use is influenced by several factors: the user’s characteristics, their environment, the website itself, and the provision of technology support. So, similar to the DIEGO model, the user, their social environment, and the characteristics of the digital intervention all influence engagement. In addition, the Ritterband et al. model starts to explore how technology factors play an important role in engagement referencing the influence of support on website use. Furthermore, this model outlines how mechanisms of change such as changes in knowledge, motivation, beliefs and efficacy mediate the path between intervention use and behavior change. These mechanisms may represent additional measures that could be included in a broad model of influences on engagement with DBCIs, as they may be more direct correlates with intervention usage than behavior change itself.

It is notable in the Ritterband et al. model that some of the mechanisms of change are also considered user characteristics (e.g, knowledge/information and cognitive factors, beliefs and attitudes, skill building and skills). This suggests that some user characteristics could be seen as motivations leading to intervention use. This harkens back to the DIEGO model, in which motivation influences how a patient makes sense of a digital intervention. In addition, a mechanism of change in the Rtterband et al. model is motivation (to change behavior). While DIEGO posited that individual-level motivation influences engagement, the Ritterband et al. model suggests engagement may also lead to changes in motivations.

The Ritterband et al. model assumes that interventions must be delivering on and gratifying motivations in order to achieve sustained use that affects mechanisms of action.

Indeed, the authors pointed out the importance of understanding motivations and patterns of Internet intervention use, particularly as compared with more traditional communication channels, noting, “People may approach and use Internet interventions differently than any other form of treatment, and it is critical to take into consideration user expectations. Users may expect to complete a limited subset of a program to satisfy their needs, whereas other users may plan and need to complete the full treatment offered. Given these different uses of an Internet intervention, it is much more difficult to make sense of usage data, as someone who appears to be a ‘dropout’ or non-adherent user may actually be someone who obtained ‘success’ with a low treatment dose” (Ritterband et al. 2009, pg. 7). Through this statement the authors underscored the importance of measuring engagement in more detail than simply measuring usage alone, as usage does not reveal the complex interactions and changes that take place to result in behavior change. Engagement is most informative when measured in concert with mechanisms of action. Through this correlation, thresholds of engagement can be determined, where we identify how much engagement on average is required to affect salient mechanisms of action that predict behavior change.

The final model reviewed here built upon past models of engagement, drawing from computer science, human-computer interaction (HCI) and behavior change literature (Figure 2.5). This model, by Perski et al., posited that engagement is a subjective experience characterized by attention, interest and affect regarding the DBCI (2016). However the authors expanded upon this dimension of engagement by suggesting user experiences can vary both within and across individuals, over time – emphasizing a dynamic nature to engagement not captured in previous conceptual frameworks.

The Perski et al. model shows a wide array of influences on engagement. They include context (individual characteristics described as the concept ‘population’ and the social environment described as the concept ‘setting’), and the intervention itself. Aspects of the DBCI are subdivided into content (whether it is based in behavior change theory) and delivery (intervention features, mode of delivery, usability, credibility and familiarity). These influences refer back to similar concepts included in the models discussed earlier in this chapter – individual, social, content and intervention features that influence engagement with DBCIs.

In addition, the Perski et al. study expanded upon Ritterband et al.'s concept of mechanisms of action. While Ritterband et al. positioned mechanisms of change as a mediator between website use and behavior change, the Perski et al. model hypothesized that DBCI engagement is a moderator in the relationship between DBCI effects on mechanisms of action. Furthermore, Perski et al. hypothesized that mechanisms of action moderate the relationship between a DBCI and engagement. These hypothesized relationships add complexity to the phenomenon of engagement, suggesting that external factors may influence engagement and in turn engagement may influence some of those factors.

In Perski's model the behavior that the intervention is targeting is also hypothesized to influence engagement. This harkens back to the DIEGO and Ritterband et al. model, where motivations influenced engagement. If the target behavior in Perski et al.'s model becomes more salient to the SBCI user, they posit this could lead to an increase in engagement. Other studies have added evidence to strengthen this relationship, finding that engagement varies by the health topic being targeted (Glasgow et al. 2011, Tatara et al. 2013). The Perski et al. model represents the most comprehensive framework to date depicting engagement with DBCIs and the proximate factors influencing this concept. It includes individual-level factor (population), social-level factors (setting), health factors (target behavior), and intervention or app-related factors (content and delivery). However, the model does not include a concept such as support or technology-level factors, as was incorporated into the Ritterband et al. 2009 model.

Technology infrastructure's influence on engagement in low and middle-income countries

While the aforementioned models incorporate myriad influences on engagement, they seem most applicable to a Western context as they assume a well-developed, stable technology infrastructure supports the functionality of the intervention. However, digital health interventions are increasingly being implemented in low and middle-income country (LMIC) contexts. While rapidly evolving technology infrastructures allow public health to leapfrog to digital strategies, this jump can present challenges for implementation. In recognition of this important contextual factor, the mHealth evidence reporting and assessment (mERA) guidelines specifically recommended reporting on population-level infrastructure available to support technology operations in locations where digital health interventions are being tested (Agarwal et al. 2016). By describing the physical infrastructure such as "electricity, access to power, connectivity, etc." corresponding to the specific context in which the intervention is deployed, researchers are afforded a comprehensive understanding of the conditions under which engagement was assessed. Technology factors underlie usability, the user experience with the technology, affect perceptions of the intervention quality and may influence public support for adapting the intervention. As a result, this factor is critical to include in a conceptual framework describing influence on engagement with digital interventions. This influence expands upon the Ritterband et al. concept of support as an influence on websites and website use, broadening the concept to reflect the myriad ways technology infrastructure influences engagement.

Synthesizing literature on influences on engagement with DBCIs within the LMIC context

Through this review we present an adaptation of Perski et al,'s model of engagement, revised to reflect factors emphasized in previous models and relevant to an LMIC context (Figure 2.6). Similar to the Perski et al. 2016 model, engagement is influenced by the population using it (individual factors), the social setting (social factors), content and the target behavior (health issue factors) and the DBCI's delivery characteristics (app factors). In addition, incorporating the mERA guidelines, the context of technology infrastructure (technology factors) is included in this simplified model of influences on engagement with DBCIs. Similar to the Ritterband et al. and Perski et al. models, this model situates engagement between the intervention itself and the mechanisms of action that predict behavior change. As with the Perski et al. model, some relationship between engagement, mechanisms of action and behavior change remain hypothesized, as there have been limited studies to assess the direction and strength of these relationships. Finally, the model includes an element of time as a reference to the O'Brien and Toms 2008 study and Ziebalnd et al. 2016 framework. In this synthesized model influences on engagement may wax and wane over time, through the phases of engagement with DBCIs, iteratively exerting influence to create a dynamic concept of engagement with DBCIs.

The following sections describe in detail each of the five factors influencing engagement with DBCIs in the final model, and the evidence that supports the relationship of these factors on engagement.

Individual factors

Individual factors comprise factors specific to the individual user of the intervention. These influences can be sub-categorized into demographic factors, psychosocial factors and technological aptitude.

Several studies have examined the influence of demographic variables such as age, gender, education, race and technology aptitude on engagement (Garvin and Simon 2017, Ben-Zeev et al. 2016, Kontos et al. 2014, Glasgow et al. 2007, Nash et al. 2015, Cunningham et al. 2014, O'Connor et al. 2016). A few have also been concerned with ethnicity and acculturation as independent variables acting on engagement. (Goyal et al. 2016, Bennett et al. 2014, López et al. 2016). A few studies targeting low-resource and minority U.S. populations and populations in LMICs have also examined how personal ownership of digital devices may play a role in engagement outcomes (Kazi et al. 2017, James and Harville 2017, Jennings et al. 2016, Pugliese et al. 2016, LeFevre et al. 2017).

Most psychosocial factors that have been correlated with engagement describe motivators intrinsic to the intervention user. These motivators vary by the individual in relative importance influencing engagement outcomes. Baseline autonomous motivation and self-efficacy to make a behavior change have been correlated with engagement (Coa and Patrick 2016, Glasgow et al. 2007), as has use of self-monitoring and other efficacy-building intervention features (Glasgow et al. 2011, Glasgow et al. 2010). These psychographic motivators are similar to gratifications of communication that were put forward by Katz, Blumler and Gurevitch (1973) and expanded upon by Ruggiero (2000). These factors include a need for timely information, need for a sense of community, perceived usefulness of the intervention, need for goal setting and attainment, need for autonomy in data entry and intervention use, and a need for entertainment.

Health issue factors

As discussed previously, engagement has been related to an individual's self-efficacy to assess and monitor as well as make behavioral changes, and this efficacy is specific to the health topic being addressed. Self-efficacy can be a particularly salient construct in predicting behavior change for certain health issues, such as physical activity. In a study encouraging daily physical activity, participants reported greater feelings of motivation, self-efficacy and achievement when using a mobile app that enabled self-tracking compared to when they used a web-based intervention without tracking features (Morrison et al. 2014). Social support can also be salient for some health topics. A study comparing engagement across interventions with only a web-based component vs. web plus phone counseling and in-person meetings found no difference in engagement with the addition of social support features (Glasgow et al. 2011), however, other studies have discussed participants' value of support features such as coaching calls and online synchronous support groups (Weiner et al. 2016, Ehlers, Huberty and de Vreede 2015) as integral to their engagement experience with digital interventions.

Engagement in DBCIs may also vary by the health issue being addressed. A study comparing engagement in similar interventions across three different health topics (healthy eating, exercise and medication adherence) found variation in the frequency with which users accessed different features (e.g., informational pages, action planning pages, self-monitoring pages etc.) by health topic (Glasgow 2011). Another study found that individual patterns of use of digital self-monitoring features varied over the long-term by health issue (comparing blood glucose, nutrition and physical activity sensors and tracking), with some individuals tracking some health issues consistently over time while others tracked more sporadically and only for specific health issues (Tatara et al. 2013). Taken together, these studies suggest personal salience of the health issue is influential on engagement.

Periodicity of the salience of a health issue may also influence engagement. Many studies note a decline in engagement over time, and a few have focused on salience as a reason for tapering engagement. One article noted that “long-term engagement with health technology does not necessarily require continuous, sustained use: routine disease management could lead to a decrease in use, until a new event occurs” (Klasnja et al. 2015, pg. 756). The DBCI may help an individual in starting to make a behavior change, and then no longer be relevant to maintaining the change. The individual may thus stop using the intervention until a new change related to the health topic is required. In a study of digital self-monitoring tool use, some participants re-engaged sporadically with glucose self-monitoring features to track out-of-ordinary situations such as dining out or travel, but otherwise did not see a benefit to integrating the intervention into daily life after an early period of learning the relationship between self-management and blood glucose levels (Tatara et al. 2013).

Social factors

There has been limited study of the role of social factors on engagement with DBCIs; however, Perski et al. hypothesized that the social environment including culture, norms, the commercial environment, media and social cues all influence DBCI engagement (2016). Studies on the acceptability of digital health records, clinical decision support tools and remote monitoring telehealth systems have found that providers are more inclined to use these systems if the use is supported by the administration through policies such as incentives for use, adequate time and staffing to monitor and use the data and compatibility of these digital systems with existing systems within the institution (Begum et al. 2013, Davis et al. 2014). Similarly for individuals using DBCIs, family and communities can shape behaviors and use of supportive tools through positive or negative reinforcement (Ritterband et al. 2009), and by contributing to the public opinion about the quality of the intervention (O'Connor et al. 2016).

App factors

The content, design and cost of the application or digital intervention all play an important role in engagement with DBCIs. Irrespective of user characteristics, there are characteristics of the intervention that can facilitate or inhibit engagement. Content quality factors include accuracy of message content, style of messages, tailoring of content to the target audience, and message development being rooted in social and behavior change communication theory. User experience also influences engagement, and this includes user burden in navigating the intervention, understandability and readability of content, instructions for how to use the intervention and the ability to use the intervention anonymously if desired (Short et al. 2015).

Extrinsic motivators also affect engagement with digital health interventions. Financial cost to access an intervention could serve as a deterrent. Incentives, on the other hand, can generate enthusiasm and may support sustained use of the DBCI, particularly if it includes gamified features (Chou 2016, Mitchell and Falkner 2014).

Technology infrastructure factors

Technology infrastructure factors influencing engagement are generally outside of an organization's ability to control but are important contextual factors to consider. These factors can be subdivided into issues related to technology infrastructure (affecting time to download the intervention, load new content, and service performance in delivering messages), data package costs to maintain intervention use, support for technical issues, and safeguards to protect privacy of user data. In a study of the MoTech program in Ghana 25% of subscribers to a text-based DBCI reported receiving messages as they were intended for delivery, suggesting that technological performance can significantly affect the potential for user engagement (LeFevre et al. 2017). In addition, several studies have discussed the financial burden of accessing DBCIs over mobile phone data or via text message services as an inhibitor to continued intervention use (Jennings et al. 2016, Swendeman et al. 2016).

Mechanisms of action

Related to psychosocial factors that may drive engagement, mechanisms of action refers to the ways in which users' psychographic profiles may change over the course of engagement with a DBCI. These could include changes in cognition/knowledge (Short et al. 2015, Ritterband et al. 2009), beliefs and attitudes, skills (Ritterband et al. 2009), accountability, motivation, and relatedness (Perski et al. 2016). In Bull and Ezeanochie's 2016 'Integrated theory of mHealth' access to DBCIs affect perceived behavioral control, and engagement can lead to mechanisms such as social network sharing, changes in social support, self-efficacy and social norms. Mechanisms of action are constructs described in classical behavior change theory, and should echo the theory that informed development of DBCI content. Psychographic changes, or mechanisms of action, can be measured as variables that depend on achieving some adequate threshold of engagement with a DBCI.

Two studies (Ritterband et al 2009, Perski et al 2016) mentioned engagement might moderate the relationship between mechanisms of action and behavior change. Only Perski et al. 2016 hypothesized a reciprocal influence of these mechanisms of action on engagement, but Ritterband et al. suggested individual cognitive factors, beliefs, attitudes and skills (indicators that were also mentioned as mechanisms of change) could influence engagement. These relationships are indicated as hypothesized in the Figure 2.6 model, as there are no studies of which I am aware that specifically measuring these correlations through a time series design.

Engagement with DBCI

The model in Figure 2.6 includes engagement with DBCIs leading to mechanisms of action and ultimately behavior change. However, it is implied that there may be some threshold 'adequate' level of engagement that must be reached in order to affect mechanisms of action. Adequate engagement itself may be a complex independent variable, since it includes how much an individual used the intervention (use metrics), how (s)he used the intervention/which features (breadth of use and feature-specific use), as well as why the intervention was used (psychosocial factors or motivations underlying engagement). An individual driven by a single reason (e.g., learning about health risks) and eager to make a behavior change may use a narrow range of features and not require much time/many visits to the DBCI in order to 'adequately' engage and change behavior. By measuring an individual's psychosocial factors driving engagement and the mechanisms of action that may have resulted from engagement, as well as measuring use metrics, we start to develop a more comprehensive understanding and measure of the concept.

Behavior change

The ultimate goal of DBCIs is to change some target health behavior. While the relationship between engagement with DBCIs and behavior change has been explored, it is difficult to make any broad conclusions from the literature. Engagement with DBCIs is defined and measured differently from one study to the next, making it impossible to compare the association of these constructs across studies.

In addition to engagement working through mechanisms of action to affect behavior change, Perski et al. hypothesize that changes in behavior could lead to further engagement with DBCIs. This relationship is indicated in the model with the use of a dashed arrow.

The model of influences on engagement with DBCIs is a synthesis of the literature. It is useful in outlining the full universe of factors that play a role in shaping engagement metrics. The most comprehensive definition of the concept of engagement may span this full image. Any metric of engagement should acknowledge that it reflects the influence of all of these factors without measuring each individually.

Conclusion

The next chapters of this dissertation will focus on explicating engagement with DBCIs and proposing a robust measure that can be used to compare engagement across studies of DBCIs. The measure will be applied in order to understand how individual factors influenced engagement within the context of the Skata mobile application for family planning in Indonesia. Finally, we challenge this model of influences by exploring experiences of engagement with the Skata DBCI. By listening to stories of Skata users, we understand how engagement led to certain mechanisms of action for family planning decision-making (e.g., knowledge and attitudinal changes, changes to self-efficacy, changes to perceived social support for contraceptive use), and what additional mechanisms may be relevant to include when measuring the relationship between engagement with DBCIs and behavior change.

Thus, this dissertation research focuses on individual and social factors that influence engagement with DBCIs in the context of family planning as a health issue, and in the country and cultural context of Indonesia. While the author acknowledges the universe of additional factors that may have affected engagement with the Skata DBCI, this dissertation is focused on a smaller subset.

Figure 2.1: Strategies to activate patients using mobile applications based on level of engagement with health care (Singh et al. 2016)
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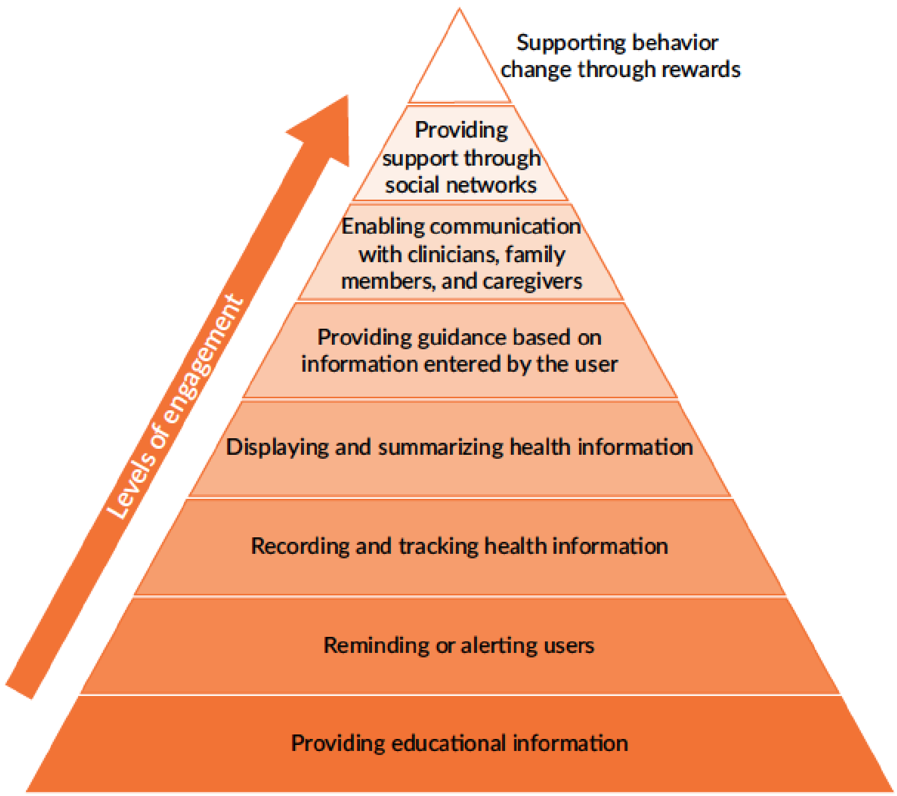

Figure 2.2: Online patient experience engagement framework (Ziebland et al. 2016)
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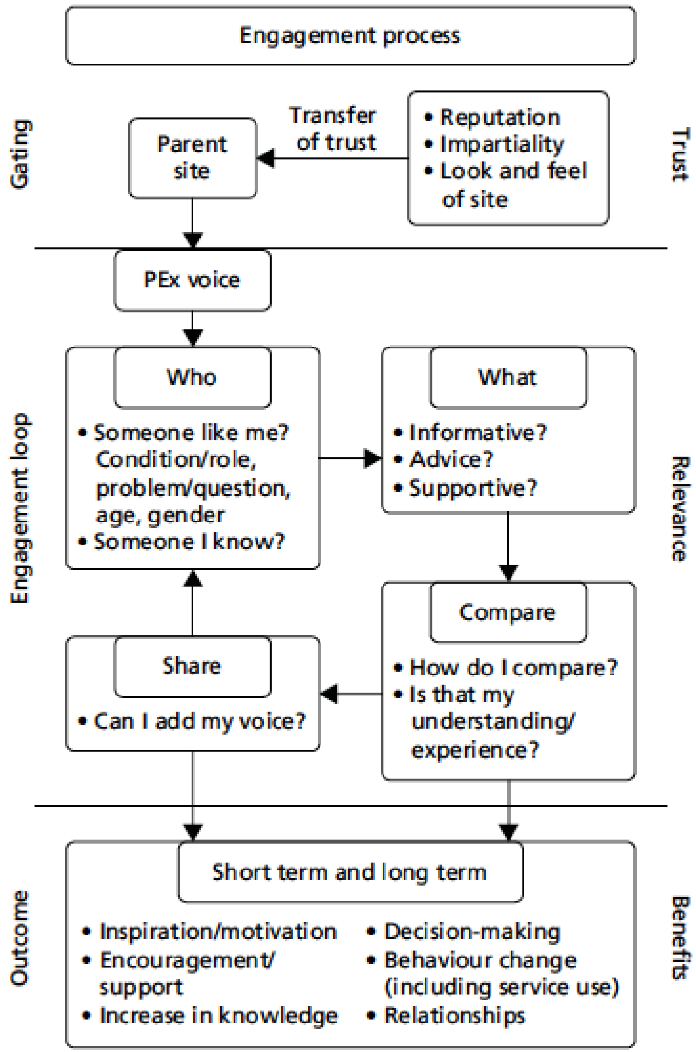

Figure 2.3: DIEGO Conceptual Model (O'Connor et al. 2016)
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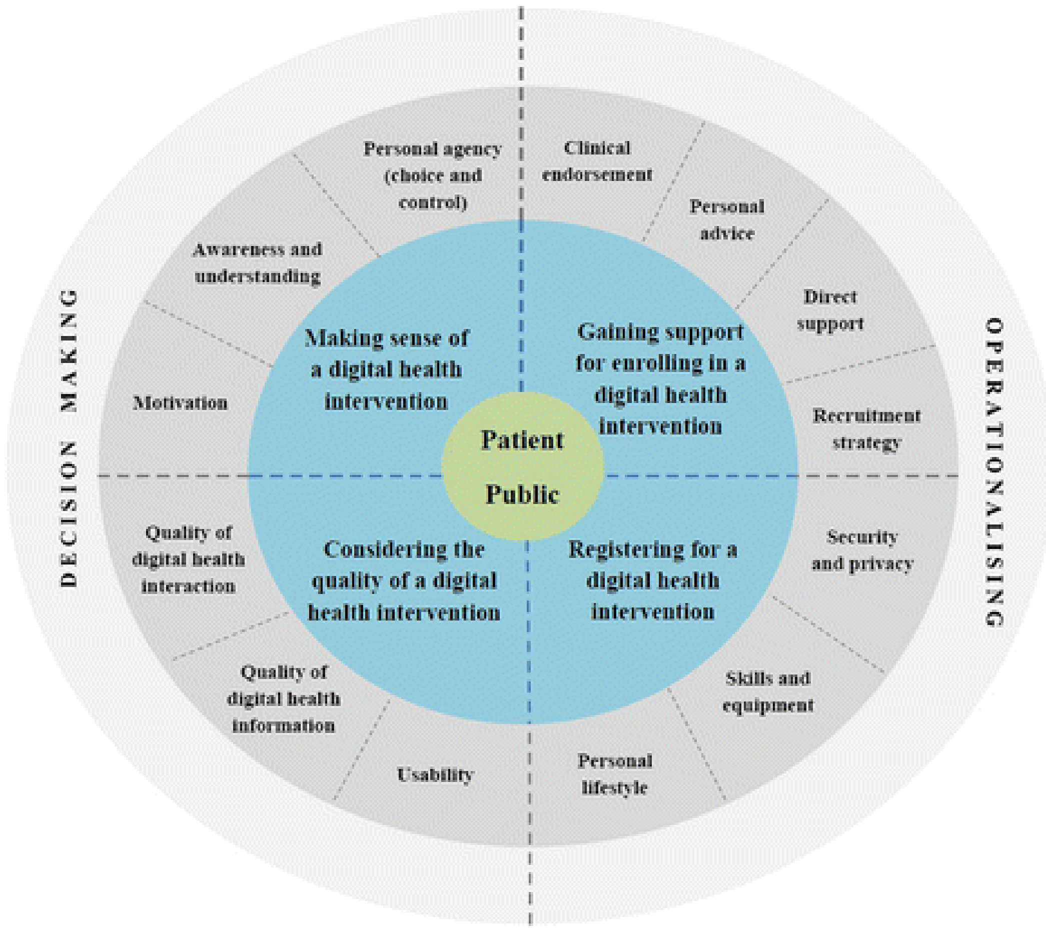

Figure 2.4: Behavior change model for Internet-based health interventions (Ritterband et al. 2009)
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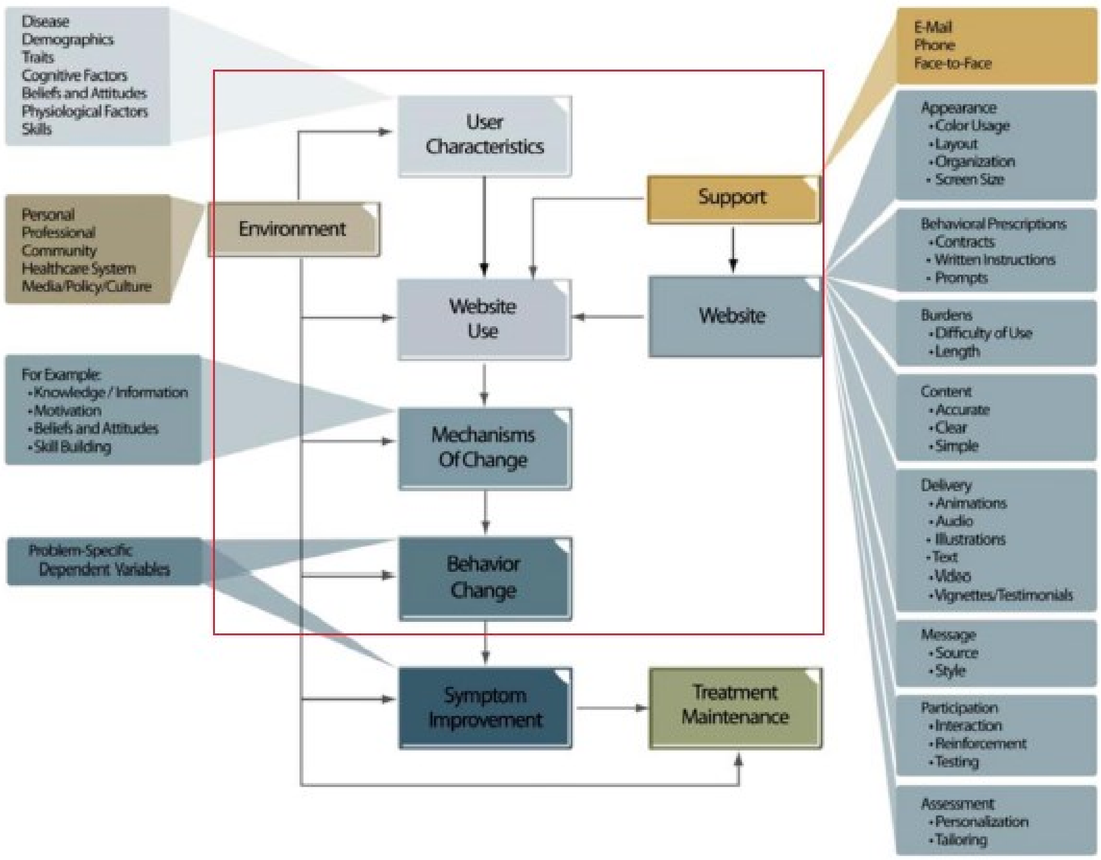

Figure 2.5: Direct and indirect influences on engagement with digital behavior change interventions (Perski et al. 2016)
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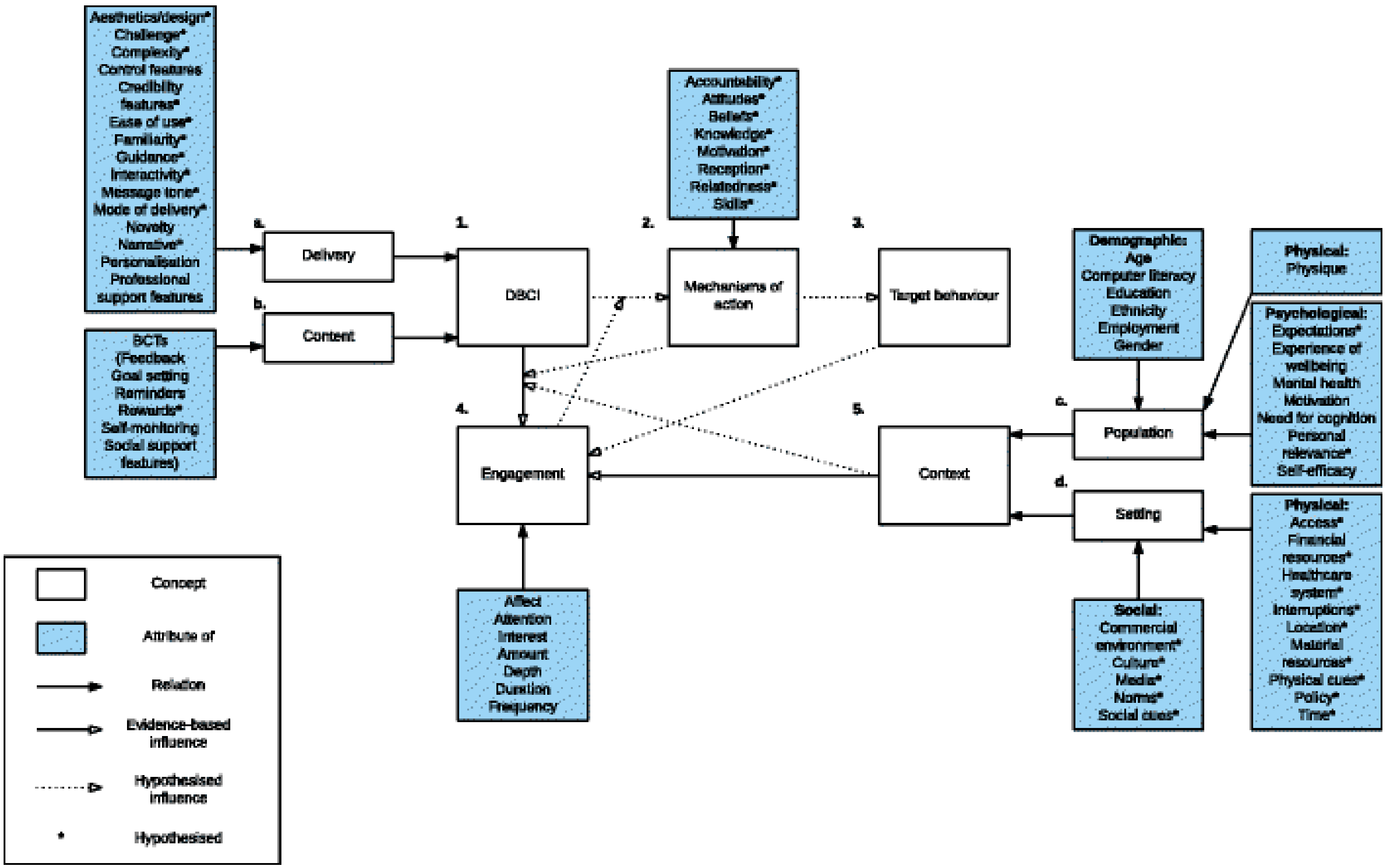
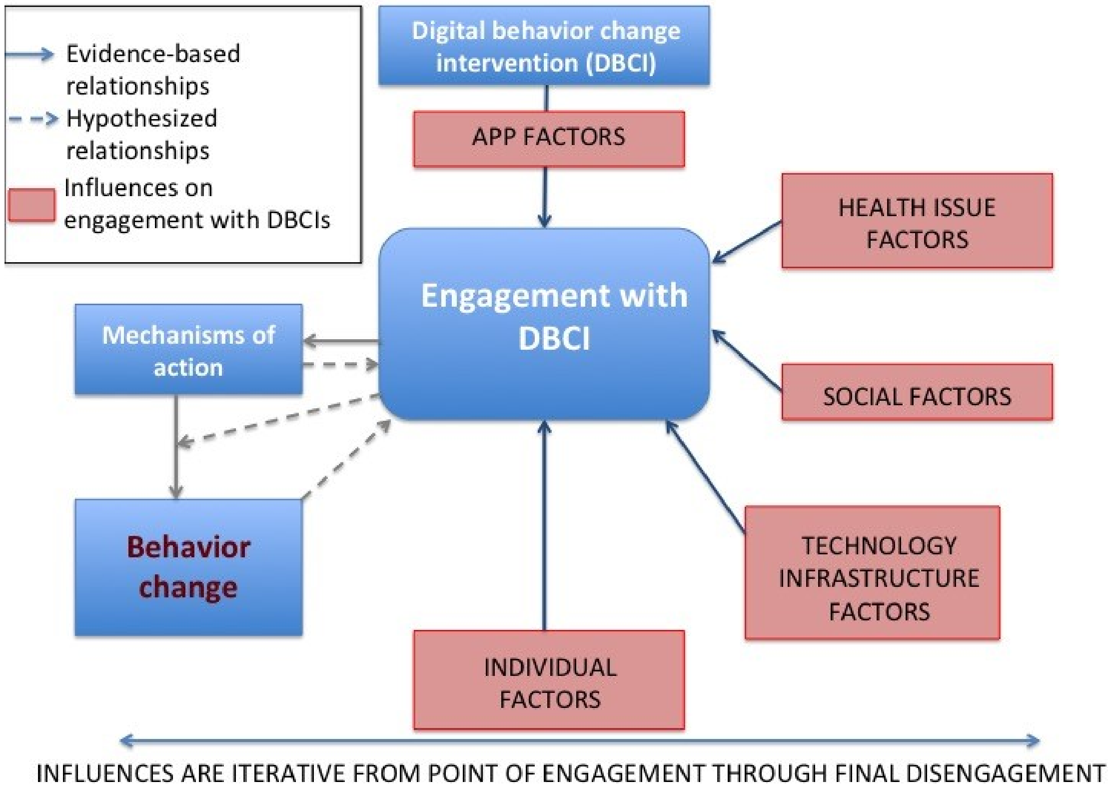


Figure 2.6: Model of influences on engagement with digital behavior change interventions, adapted from Perski et al. 2016



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Chapter 3: A concept explication to define and measure engagement with digital behavior change interventions

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Chapter 3 – A concept explication to define and measure engagement with digital behavior change interventions – proposing the Extended Engagement Index

Abstract

Engagement is an important variable to measure as part of the evaluation of digital behavior change interventions (DBCIs). The concept itself has three dimensions: cognitive, emotional, and behavioral. Within the behavioral dimension, which is the focus of this paper, the concept can be further parsed into phases of engagement: from the point of engagement, through the period of engagement to disengagement and potentially re-engagement. Looking more closely at the period of engagement in particular, there is a great heterogeneity in the indicators that are used to describe various facets of engagement overall with a DBCI, and with individual features within complex DBCIs. By considering re-engagement as a phase we also underscore that time is a fundamental variable of interest for engagement. However, engagement metrics commonly treat the concept as static or independent of time, rather than dynamic, or time-dependent. Re-engagement indicators illuminate how engagement may wax and wane. Through a review of measures used to describe engagement with DBCIs, this paper recommends a collection of indicators called the Extended Engagement Index to comprehensively measure the dimensions, phases and various facets of engagement.

Introduction

Although there is limited literature evaluating the concept to date, engagement is a fundamental concept for digital health evaluation. Compared to traditional media interventions, digital and behavior change interventions (DBCIs) uniquely place the audience in control of their exposure to messaging. The audience is in charge of the intervention medium (e.g., computer, mobile phone, tablet, etc.) and takes an active role in creating the communication experience. In this active media consumption model, a major challenge to changing behavior is users' common and substantial drop-off in using these interventions (Wanner et al. 2010).

Engagement is a process through which mechanisms of action predicting behavior change vary. Bull and Ezeanochie 2016, in their Integrated theory of mHealth posit that engagement is a necessary precursor for DBCI programs to lead to the psychosocial changes described in classic behavior change models. Psychosocial constructs include interpersonal communication through social network sharing, social support, self-efficacy, and perceived social norms in their model; however, the specific psychosocial constructs affected depend upon the behavior change theory used to inform the DBCI design. As such, engagement may also lead to changes in constructs such as knowledge, attitudes and cues to action, among other constructs that have been described in classical behavior change theory to predict behavior change and ultimately change to health outcomes.

By understanding the concept of engagement and operationalizing it fully, researchers can build the evidence base on the effects of DBCIs on health behavior. Given the growing financial and human resource investments in development and implementation of DBCIs, particularly in low and middle-income countries, it is imperative that we conduct rigorous evaluation of these interventions. Engagement stands at the center of evaluation models, and thus needs to be carefully, consistently defined and measured.

Methods

The concept explication process was used to understand how typical measures of engagement from the literature compare to the totality of the concept. A concept explication is a detailed review of the literature to understand how a concept has been discussed and measured. The process reveals any variability that may exist in definitions of the concept and its operationalization within the literature. It also consists of a reflective process through which the measure is carefully considered in one's research context to better define the focal concept. This process makes transparent the commonalities and differences in how a contested concept is being discussed and measured, helping to form consensus and ensuring that operationalization of a concept follows from a carefully constructed definition and not vice versa. The basic stages of a concept explication are (Chaffee 1991):

1. Identify a focal concept
2. Provide a literature review
3. Provide a meaning analysis
4. Provide an operational definition
5. Describe the concept's relevance to one's research

This concept explication reviews the digital health literature to illuminate the variability in definitions of the term "engagement" and subsequently in its operationalization. Using Chafee's (1991) methodology, this study synthesized the varied definitions into a proposed, comprehensive definition of the concept with linked measures.

To explore first the concept of engagement, we included reviews that substantively reflected on the concept of engagement through several paragraphs of description. Six peer-reviewed articles were identified to inform the findings on the concept of engagement.

A second, broader literature review was conducted to elicit operationalizations of engagement in the literature. This review process followed a series of criteria to increase the homogeneity of the concept being measured, within certain explicit boundaries.

Digital health is defined as the use of SMS texting programs, self-monitoring devices, online sites, social media, and mobile phone and portable device applications throughout the healthcare utilization experience (Ranney et al. 2016). Digital health interventions span a broad array of purposes: from increasing efficiencies in a health system to aiding data collection, supporting service provision to increasing client/patient participation in health decisions and health maintenance. Here, we constrain the focus of the engagement concept to digital *behavior change* interventions. Specifically, we examine customer-facing DBCIs used in non-clinical settings. This excludes provider-facing interventions or interventions that support caregiver communication with providers. Customer-facing interventions used in non-clinical settings are most likely to be used voluntarily. While healthcare providers and members of their social network may encourage the adoption of a DBCI, participants are not required to use these DBCIs to make behavioral changes. Comparatively, use of provider-facing DBCIs may be mandated by workplace policies, and use of caregiver-facing DBCIs may be motivated by duty to ensure quality care for patients. Furthermore, this study focuses on DBCIs that are used by the general public, not individuals with a particular health diagnosis who may be prescribed to use the intervention. These boundaries were set to ensure that the concept of engagement measured voluntary interaction of participants with DBCIs in natural settings.

The Transtheoretical model (TTM) (Prochaska and Velicer 1997) was also used to define the parameters of this literature review. The TTM posits that an individual progresses through stages of psychosocial change on the path towards changing an ongoing health behavior. The stages are: precontemplation, contemplation, preparation, action, maintenance and termination when individuals have formed a habit that is unwaveringly part of their daily life. In each stage, individuals exposed to an intervention may experience some psychosocial changes or mechanisms of action that propel them into the next stage. This model incorporates the concept of time for behavior change to occur, which underscores how a process of engagement can undergird progression through the stages. In addition, the TTM is typically applied to behaviors that require sustained change that can be maintained or discontinued, resulting in individuals repeating their journey through stages leading to the behavior change.

Applied here, individuals who download or access a DBCI would already be beyond the TTM phase of pre-contemplation to make a behavior change. We assume that they access the DBCI out of a desire to make the behavior change. Upon first accessing the DBCI, individuals may still be gathering information to contemplate the change, prepare for making the change, or they may be seeking support as they start to take and sustain an action. These stages from contemplation to action and early maintenance mark a period during which DBCI users may be undergoing great shifts in psychosocial indicators associated with the intervention and behavior, and where engagement with a DBCI may be most salient and dynamic.

Taken together, these criteria form boundaries around the types of DBCIs considered when operationalizing engagement. For example, per these criteria, studies on engagement with electronic health record systems are not considered in this study. These DBCIs are excluded because they are largely used in clinical settings, are provider-facing, and support one-time treatment decisions rather than an ongoing behavioral change. Interventions such as medication adherence support programs are also not included in this study. Adherence behaviors primarily support routinized maintenance of a behavior rather than making a concerted change, and thus they fall outside of the TTM boundaries of interest for this study. Interventions that are included in this study include, for example, a mobile application to encourage eating a healthier diet. This change is one that is ongoing in a customer's life, requires progression from contemplation to action, happens in a non-clinical setting, and the choice to use a DBCI to support the change is likely voluntary.

In addition, the inclusion criteria require that studies informing the operationalization of engagement with DBCIs place substantive focus on engagement, applying some metric for engagement to an actual intervention. Substantive focus is defined as at least one paragraph describing the engagement measure. These criteria eliminate thought pieces that discuss engagement but do not apply a specific engagement measure and ensure that all studies include specific indicators utilized as a proxy for engagement.

By setting forth constraints on the studies included in this concept explication, we ensured some homogeneity to the operationalizations of engagement reviewed. In summary, the inclusion criteria employed in this literature review were:

1. Studies of *digital* health interventions,
2. Studies conducted in *non-clinical* settings,
3. Studies of *customer-facing* DBCIs intended for use by the general public,

4. Studies of DBCIs that *supporting health decision making* to move users through stages of change from contemplation to preparation, action and early maintenance, and
5. Studies with a substantive focus on engagement, including *application of a metric of engagement to an intervention*

This literature review was conducted in 2016-2017 on the PubMed and Communication and Mass Media Complete (CMMC) databases and supplemented by grey literature recommended by experts or included in online databases such as the mHealth evidence database (mHealthEvidence.org) and the Human Computer Interaction Bibliography (HCIbib.org). The choice of databases was determined based on the multi-disciplinary nature of digital health for social and behavior change communication (SBCC). Included literature spans January 1, 2005 to February 14, 2017. The 2005 cut-off the literature reviewed was determined based on the frequency of the term engagement in the literature by year. In a PubMed search of the literature, there was a marked increase in publications about engagement in digital health decision-support tools starting around 2007, shortly before launch of the iPhone, one of the first widely-used phones to include mobile applications (Figure 3.1). So as not to miss any early literature on engagement, 2005 was selected as the starting year for this literature review.

Three main concepts were used in creating search terms for this review. The first focal concept included two alternatives: one focused on digital health and another focused on health decision support. The first alternative employed Medical Subject Heading (MeSH) terms synonymous with telemedicine and telehealth along with commonly used terms such as mobile health and mobile app. The second alternative also employed the MeSH term for health along with a search term for decision support. The purpose of creating two alternatives for the first focal concept was to capture a full array of digital health interventions while limiting those reviewed to interventions that assist in behavior change. The second focal concept was engagement, and included terms about customer engagement and patient activation, as these terms are used synonymously in the literature to discuss the complex phenomenon of patient engagement in digital health interventions for SBCC. (See Appendix 2 for search terms used per each database.)

Records identified through the search terms were assessed first through a review of titles and abstracts to determine whether they met the inclusion criteria. If a determination could not be made based on the title and abstract alone the full text of the article was reviewed. The search flow is depicted in Figure 3.2. The results of these search strategies are presented in Table 3.1. A total of 69 articles, reports and conference proceedings were found relevant to cataloguing operationalizations of engagement. Applying the aforementioned eligibility criteria, a total of 1,299 articles and other documents were deemed irrelevant to this study.

Results

Concept

Six studies were identified that deeply reflected on the concept of engagement. These were: Patterson, Yu and de Ruyter 2006, Brodie et al. 2011, Barello et al. 2016, O'Connor et al. 2016, Gallivan et al. 2012, and O'Brien and Toms 2008. The studies represent a variety of disciplines but converge on a description of three main dimensions of engagement. Behavioral engagement, one of the three dimensions, is further parsed into four phases.

<u>Three dimensions of engagement</u>

The concept of engagement has been explored in organizational engagement (Patterson, Yu and de Ruyter 2006), customer engagement (Brodie et al. 2011), patient engagement (Barello et al. 2016) and digital health engagement (O'Connor et al. 2016). From these reflections on engagement, three dimensions of engagement have been suggested: cognitive engagement, emotional engagement and behavioral engagement.

Cognitive engagement concerns the understanding of the engagement object. In organizational engagement, cognitive engagement is defined as the level of concentration focused on an organization, or absorption by the organization (Patterson, Yu and de Ruyter 2006). In patient engagement cognitive engagement is a change in what the patient thinks and knows, and how (s)he makes sense of the disease (Barello et al. 2016). In the Digital Health Engagement (DIEGO) Model, patients must make sense of a digital intervention, assessing their own motivation to use the intervention, their awareness and understanding of the intervention, and their personal agency to use the intervention (O'Connor et al. 2016). We may consider this realm of engagement in DBCIs to cover topics such as knowledge or awareness of the DBCI and perceived acceptability of the DBCI in one's daily life.

Emotional engagement concerns how users feel about the engagement object. In organizational engagement, emotional engagement is described as the individual's sense of belonging to the organization, or dedication to the organization (Patterson, Yu and de Ruyter 2006). Patient engagement describes emotional engagement as connected to what the patient feels about the disease and his/her life condition linked to it (Barello et al. 2016). The DIEGO Model describes this dimension of engagement as focused on assessing the quality of the digital health intervention in terms of usability, interaction and content. Indicators of emotional engagement with DBCIs may focus on usability, satisfaction and recommendation to others. While an individual may have strong cognitive engagement with a DBCI – knowing about it and perceiving it as acceptable – they may have low emotional engagement if they personally do not enjoy the intervention.

Behavioral engagement is about the interaction between the user and the engagement object. In organizational engagement this dimension is defined as the level of energy spent and interaction that takes place between the individual and organization. Patient engagement describes behavioral engagement as what patients do to face the disease condition. While this dimension of engagement is considered the crux of patient engagement, it is not described in the DIEGO model, which focuses on factors that influence initiation of engagement with a DBCI. Behavioral engagement is considered a dynamic, interactive and iterative process where the individual plays an active and meaningful role in planning and decision-making for health services that affect their lives (Gallivan et al. 2012). User-system interaction can be further parsed into phases as described by O'Brien & Toms in their examination of engagement in technology (2008).

Phases of behavioral engagement

Behavioral engagement with technology can be broken into four stages: 1) the point of engagement, 2) a period of sustained engagement, 3) disengagement, and 4) re-engagement (O'Brien and Toms 2008). These phases reflect how engagement is a dynamic process and incorporates a sense of time.

At each phase of engagement, one can describe attributes of the users who are involved with the technology, the technology system, and the interactions between the user and system. The point of engagement describes how an engaging experience began. It may reflect motivations for initiating engagement and the point at which the DBCI resonated with a participant's interests. The period of engagement describes what is taking place when a user focuses their attention on the DBCI. It reflects the ways in which a user's interest is maintained by the DBCI. Disengagement describes the moment when a participant makes an internal decision to stop using the DBCI. Disengagement can be brought about for a variety of reasons, such as the DBCI content is no longer urgently needed, the content no longer commands interest, or external factors interrupt or prohibit continued engagement. Finally, re-engagement is resumed engagement with the DBCI after temporarily dropping off or periodic engagement over time. This phase suggests that some engagement may be episodic. Re-engagement may be driven by cues to return, personal need or desire to return, incentives to resume engagement, or improvement to the DBCI system allowing re-engagement of those whose use was interrupted. Re-engagement can be captured over the short-term and long-term.

Measures

Interactions between the user and DBCI system are the focus of engagement metrics. A figure summarizing the studies that informed this review of operationalizations is included as Figure 3.3.

Cognitive and emotional engagement measures include indicators assessing awareness, acceptability, usability, satisfaction and willingness to recommend. These indicators are typically collected through population and user surveys and qualitative methods such interviews, usability testing and focus groups.

Behavioral engagement measures describe the process of interaction between the user and the DBCI across four phases: point of engagement, period of engagement, disengagement, and re-engagement. Indicators of behavioral engagement are particularly important to study as many of them can be gleaned from the data created as an artifact of subscribers' use of DBCIs. In this paper we refer to these data tracking the movement of a subscriber through a DCBI as 'data exhaust.' Compared to self-reported data that is collected retrospectively, data exhaust is captured unobtrusively and in real-time. Thus, data exhaust is more objective than engagement data that relies on the accuracy of a user's memories. Data exhaust may include databases of comments made, calls or messages sent; however, we refer to databases that require a textual analysis by name. The concept of data exhaust is thus restricted to actions that may be tracked quantitatively.

DBCI programs must work with the intervention development team to pre-determine which data exhaust indicators and databases to track through a dashboard mechanism, sometimes called routine service logs. The collaboration optimally occurs during the design phase of an intervention, allowing the full suite of relevant engagement data to be collected prospectively. If indicators are not defined during the design phase of DBCI development, it is possible that these data may not be tracked and would be unavailable for later analysis. In addition, it is important to be cognizant of how the information architecture of an intervention, or the way in which the information is organized, may influence usage patterns. For example, a DBCI can lead users through a 'tunnel,' or step-by-step process, be laid out in a 'matrix' where users explore the information freely, or through a 'hierarchical design,' in which users drill down to access increasingly detailed content (Danaher et al. 2015). Each design has implications for tracking data such as page visits and certain pages may be 'buried' within the architecture or only accessible once the user has reached some threshold of use, so interpretation of page visits must consider the information architecture as a critical contextual element.

Cognitive and Emotional engagement

Five studies in this review included example indicators that measure the cognitive and emotional dimensions of engagement (Table 3.2). Cognitive engagement indicators focused on acceptability (Morisson et al 2014, Tatara et al 2013); this review did not find any studies that included indicators of awareness of DBCIs. Emotional engagement indicators captured in this review focused on satisfaction (Quintilliani et al. 2016, Taki et al 2017, Partridge et al. 2016) and willingness to recommend (Quintilliani et al. 2016) but did not include studies of usability. Studies assessed cognitive and emotional engagement through a variety of mechanisms, including closed-ended user surveys, interviews and focus group discussions.

Only a few example cognitive and emotional engagement measures are included in Table 3.2 because this literature review does not focus on exploring measures of cognitive and emotional dimensions of engagement with DBCIs. Rather, the majority of this paper catalogues the variety of behavioral engagement indicators that have been found through this literature review.

Behavioral engagement

Behavioral engagement indicators measure interaction between the user and DBCI. Thus, they offer the most opportunity for operationalizing the concept of engagement using unobtrusively collected data exhaust.

Behavioral engagement indicators are broken into phases of behavioral engagement, referencing O'Brien and Toms' 2008 conceptualization of engagement. During each phase of behavioral engagement, indicators measure a variety of facets of the engagement process. 'Facets of engagement' synthesizes and summarizes the collective phenomenon that each study indicator measured (e.g., reaching a threshold, length, breadth, depth of passive or active engagement, emotional quality of engagement or describing the dynamic nature of engagement). Figure 3.4 summarizes the facets of engagement that were identified through a review of indicators used to measure each phase of behavioral engagement.

Tables 3.3 – 3.5 provide more detail about the indicators identified in this review of operationalizations of behavioral engagement with DBCIs. The studies from which these specific indicators were identified are noted. A synthesized summary of what the specific indicators are measuring as a collective is termed 'facets of engagement phase.' Indicators are categorized by type (binary or continuous) and include notations to indicate whether they assess overall DBCI use or use of a specific feature.

Point of engagement

Eleven studies mentioned behavioral engagement indicators focused on the point of engagement (Table 3.3). The data were primarily collected from data exhaust, however one study required reconciling a potentially separate database of baseline data with the data exhaust from the DBCI.

Many point of engagement indicators are binary indicators either assessing point of engagement for the DBCI overall or point of engagement for a specific feature within the intervention. They measure the number of users who reach some threshold for initial engagement with the DBCI (Mattila et al. 2013, Nash et al. 2015, Estrada et al 2017, Buis et al. 2013). These indicators serve as performance metrics for the DBCI program, indicating how many users reached some initial engagement threshold, with feature-specific binary indicators focusing on initial engagement thresholds that may be particularly salient in predicting behavior change (Nash et al. 2015, Penchman et al. 2015, Buis et al. 2013, Glasgow et al. 2007, Mattila et al. 2013, Dennison et al. 2014, Helander et al. 2014, van Drongelen et al. 2016, Wiener et al. 2016). The Danaher et al. 2006 indicator measuring the length of time for achieving point of engagement is a unique performance metric that may not be relevant for all programs, depending on the program's enrollment strategy.

Period of engagement

In this literature review, 55 studies offered some indicator to measure the period of engagement (Table 3.4). The variety of measures identified indicates that there are many facets of engagement to measure during this phase. Unless otherwise noted, these indicators are derived from analysis of data exhaust.

Threshold of engagement measures of the period of engagement were primarily binary indicators. These indicators measure number of users who reached some threshold of engagement with the intervention beyond initial use (Heminger et al. 2016). Some of the thresholds set a low standard for interaction with the DBCI over the period of engagement such as remaining a subscriber or returning once (Heminger et al. 2016, Nash et al. 2015), while others set high targets for period of engagement thresholds with the DBCI overall or with a specific feature such as daily use or complete adherence to a feature (Nijland et al. 2011, Mattila et al.2013, Scherer et al. 2017, Shapiro et al. 2010, Estrada et al. 2017, Buis et al. 2013, Staffileno et al. 2015). A few of the indicators outlined a threshold that would indicate 'adequate' engagement with a specific feature such as completing core modules or a majority of sessions (Dennison et al. 2014, Zeng et al. 2016, Wilson et al. 2017, Fontil et al. 2016, van Drongelen et al. 2016). Adequate engagement may be a complex independent variable to determine, as it may depend upon the motivation driving engagement. In these studies, adequate engagement was an amount of engagement hypothesized by the program to be enough interaction with a feature conceptually linked to some mechanism of action that predicts behavior change, so that engagement would affect a measurable psychosocial shift. While adequate engagement with specific features is measured, adequate thresholds of engagement with a DBCI overall are not used. This is reasonable since many DBCIs have multiple features, and each may be related conceptually to a distinct mechanism of action.

Depth of engagement is an extension of the threshold for engagement facet. All non-threshold depth of engagement indicators were continuous and they were applied to the DBCI overall, to a subsection of the DBCI, or to specific features. Overall depth of engagement indicators counted the number of visits and/or logins, length of time using the intervention over all sessions or per session (Danaher et al. 2006, Richardson et al 2013, Kuijpers et al. 2016, Bush et al. 2017, Scherer et al. 2017, Anderson et al. 2016, Glasgow et al. 2011, Partridge et al. 2016, Serrano et al 2017, Moin et al. 2015, Short et al. 2017, Heminger et al. 2016). DBCIs often focus on a single health topic, but some may include tools to change health behaviors connected to inter-related health issues. Studies of multi-topic DBCIs used continuous indicators to measure depth of engagement in each topic area, allowing researchers to compare user needs for support and DBCI success in provision of support across health topics (Danaher et al. 2015, Tatara et al. 2013).

Feature-specific depth of engagement indicators introduced further ways to parse out depth of engagement during the period of engagement. Many studies measured depth of engagement as progress towards completing a program goal such as all modules available in the DBCI (Dennison et al. 2014, Danaher et al. 2015. Turner-McGrievy & Tate 2014, Moin et al. 2015, Goyal et al. 2016, Short et al. 2017, Kornman et al. 2010, Partridge et al. 2016, Lin et al. 2015, Grutzmacher et al. 2017, Scherer et al. 2017, Quiltilliani et al. 2016). Some indicators measure depth of *passive* engagement, tracking visits to a page or feature (Hales, Davidson & Turner-McGrievy 2014, Partidge et al. 2016, Heffner et al. 2015, Brusk & Bensley 2016, Kuijpers et al. 2016, Lin et al. 2015, LeFevre et al. 2017). Other indicators focus on depth of *active* engagement with a feature, counting only interactions that require additional user action such as liking a post, posting a comment, making a data entry or sending a message (Danaher et al. 2006, Stellefson et al. 2013, Turner-McGrievy & Tate 2014, Moin et al. 2015, Padman et al. 2013, Turner-McGrievy & Tate 2013, Penchamn et al. 2015, Wang et al. 2016, Merchant et al. 2014, Tague et al. 2014, Glasgow et al. 2011, Heffner et al. 2015, |Short et al. 2017, Ehlers, Huberty & deVreede 2015, Mamykina et al. 2016, Goode et al. 2015, Christofferson et al. 2016, Goyal et al. 2017, Quiltilliani et al. 2016, Owen et al. 2016, Kato-Lin et al. 2015, Capozza et al. 2015). Distinctions between active and passive engagement may be particularly relevant in DBCIs that include both push and pull features. For example, in a one-way text-messaging program, the DBCI design does not allow participants the opportunity to actively engage. One study particularly interested in the difference between passive and active engagement interviewed a subsample of its users and found 40% of them reported "lurking" on the DBCI social media pages – visiting, but not taking any action to demonstrate engagement (Merchant et al. 2014).

Length of engagement was measured with continuous indicators tracking the length of overall DBCI use (Du et al. 2016, Serrano et al. 2017, Buis et al. 2013, Kim et al. 2016, Danaher et al. 2006, Richardson et al 2013, Kuijpers et al. 2016, Bush et al. 2017, Scherer et al. 2017, Anderson et al. 2016, Glasgow et al. 2011, Partridge et al. 2016, Moin et al. 2015, Short et al. 2017, Heminger et al. 2016) as well as length of use for specific features (Taki et al. 2017, Danaher et al. 2006, Brusk & Bensley 2016, Owen et al. 2016). Unit of measurement becomes salient when measuring length of engagement, as some DBCIs are able to differentiate between subscribers who visit versus those who log into the DBCI. Some log files and analytic software can track users by IP address or other unique user identification numbers (ID) that do not require login, and allow the system to capture counts of repeat visitors, affording the potential to calculate number of visits per unique ID. Typically, a DBCI may require login to ascribe a unique ID to a user. Some DBCIs have some public content while other content requires login.

The design of the DBCI will determine whether there is a difference in tracking visits versus logins and inform the development of the data exhaust tracking mechanism.

Breadth of engagement was measured with both binary and continuous indicators. Breadth of engagement was concerned with measuring whether the user engaged with multiple parts of the DBCI, suggesting the user interacted with a variety of communication features addressing a range of psychosocial factors that predict behavior change for the specified health topic. By definition breadth of engagement indicators measure the DBCI overall, assessing the volume of unique features accessed. Binary indicators measured the number of users who achieved some threshold breath of engagement (Owen et al. 2016). Continuous indicators measured breadth to potentially understand whether user motivations and needs varied over time, and whether all aspects of the DBCI were equally valuable to users (Partridge et al. 2016, Danaher et al 2015, Zeng et al. 2015, Richardson et al 2013, Stellefson et al. 2013, LeFevre et al. 2017, Glasgow et al. 2011).

Just two studies included indicators that assessed emotional quality of engagement during the period of engagement. These quality measures focused on feature-specific use. Both studies offered a threshold indicator for assessing engagement quality using qualitative methods: reviewing the content of SMS responses and social media posts to determine whether they are related to the original prompt and reviewing the timing of the SMS/post to determine whether it was a response or spontaneous interaction with the DBCI (Kornman et al. 2010, Penchman et al. 2015). One study proposed two additional feature-specific indicators of engagement quality that assessed the urgency of interacting with the DBCI through the response time to reply to a pull message, and the level of familiarity users seem to use when interacting with the DBCI indicated by the use of shorthand language or emoticons in pull message responses (Kornman et al. 2010). These indicators may be particularly salient for DBCIs that include interactive communication features, and for health topics in which social support and social norms are important psychosocial predictors of behavior change.

Disengagement and Re-engagement

In this literature review, six studies offered some indicator to measure the behavioral engagement phase of disengagement during the study period (Table 3.5). Disengagement is considered synonymous with dropout in the literature and may indicate that a user did not achieve the 'adequate' threshold of engagement if DBCI programs expect users to remain engaged for the full study period (Lie et al 2017, Buis et al. 2013, Mitchell & Faulkner 2014, Chaplais et al. 2015, Coa & Patrick 2016, Goldstein et al. 2017). Disengagement, however, can be a misleading indicator if study periods are shorter than the window for which users may re-engage with the DBCI.

Re-engagement indicators help illuminate the dynamic nature of behavioral engagement with DBCIs. This review included only nine studies that offered an indicator to measure re-engagement and described the dynamic nature of engagement as a concept. Most measured the number of visits through a time series, allowing number of visits to be captured as a dynamic indicator that may fluctuate throughout the study period (Danaher et al. 2006, Mamykina et al. 2016, Milani et al. 2017, Kim et al. 2016, Muuraiskangas et al. 2016, Puszkiewicz et al. 2016, Scherer et al. 2017, Glasgow et al. 2011). One study, however, went a further step to average the time series measurements and create a summary re-engagement measure that weighed each time period equally (Taki et al 2017). The is a small number of studies that capture re-engagement is surprising given that the dynamic nature of engagement is an important aspect of the concept. Re-engagement measures underscores how engagement is a process that changes over time. Like disengagement, re-engagement measures are constrained by the period of study. However, the period of study may need to be significantly longer to capture re-engagement if the salience of the health topic is episodic. Re-engagement measures were generally continuous depth of engagement measures, recorded in a time series.

The Extended Engagement Index: A comprehensive metric of engagement

The Engagement Index (EI) developed by Peterson and Carrabis (2008) and adapted and applied by Taki et al. (2017) offers one of the most comprehensive metrics describing engagement with digital interventions. The Taki et al. EI included five subscales: click depth, loyalty, interaction, recency and feedback (Table 3.6). The click depth index measured the number of pages a participant views per day and calculates how many days the user viewed at least two pages out of their total number of sessions. Loyalty measured how frequently the user accesses the DBCI during the study period and is calculated as indicated in Table 3.6. Interaction measured the number of push notifications opened out of those sent by the program. Click depth, loyalty and interaction were all calculated for three distinct time periods over the course of the Taki et al. study: initial use (0-3 months), interim use (3-6 months) and the final period of use (6-9 months). This time series approach helped to illuminate the dynamic nature of engagement on each subscale. Recency measured the time that elapses between sessions of use and is calculates as indicated Table 3.6. Recency was also calculated for three time periods: the time between registration and initial DBCI use, interim use (3-6 months) and the final period of use (6-9 months). The final subscale of the Taki et al. EI was feedback, gathered through 37 questions in a close-ended survey of users to gauge satisfaction, usability, perceived quality and utility of content, and willingness to recommend the DBCI. The data were coded for positive responses then summarized in a score reflecting a rate of positive response for the feedback survey. The five subscale scores were finally added together and multiplied by 100 to generate an overall engagement score.

The Taki et al. EI subscales measured a variety of facets and phases of engagement. Specifically, the click depth (CD) subscale is a measure of depth of engagement. The loyalty (L) subscale is a measure of the length and frequency of engagement. Length of engagement describes the time from the point of engagement through period of engagement until disengagement during the study period. Frequency of engagement describes depth of engagement in the overall DBCI as a facet of the period of engagement. The interaction (I) subscale is a measure of feature-specific depth of use. The recency (R) subscale measured point of engagement in its first time period and highlighted the dynamic nature of engagement with measures taken at subsequent time periods. Finally, the feedback (F) subscale is a measure of emotional engagement with the DBCI.

The Peterson and Carrabis EI included two additional subscales: brand (B) and duration (D). The brand index measured the level of attention participants were paying to the brand/specific DBCI just prior to accessing it. These data typically come from analytic packages such as Google Analytics, and track search sessions and click streams leading users to the DBCI. The data suggest the level of involvement participants have with the brand or specific DBCI. The authors hypothesized that participants who searched specifically for the DBCI or navigated to it through partners who recommended it may have the highest brand engagement, while those who arrived at the DBCI through a general search for the topic area may have lower brand engagement, and those who arrived at the DBCI through less intentional means may have comparatively little brand engagement. Brand engagement is measured, however, by assessing the percentage of users who clicked through to the DBCI depending on their search phrase. As such, it is not a person-level index like the others in the EI. Given its focus on involvement, it is also less aligned with the dimensions, phases and facets of engagement described in this concept explication. The duration subscale measured the average length of time a participant spent per visit to the DBCI. Like click depth, this is a measure of the attention the participant gave to the DBCI. Typically, these data can be garnered through data exhaust and are calculated by averaging duration times per visit over all the visits in a time period, taking a time series approach to measuring the index. Taki et al. did not include brand and duration subscales in their application of the EI because they did not have access to the data required to calculate these indices.

To increase the sophistication of DBCI evaluations, this paper proposes the Extended Engagement Index (EEI). The EEI extends Taki et al.'s adapted EI, adding Peterson and Carrabis' duration subscale and includes new subscales for cognitive engagement (CE), feature-specific use (FSU) and feature breadth (FB). The EEI also includes recommendations for data collection over a time series. With these additions the EEI is able to measure all dimensions of the engagement concept, as well as numerous facets across all phases of behavioral engagement. The EEI, if widely adopted, would address the problem of heterogeneity of engagement data across DCBI evaluations. While past comparisons of engagement across DBCIs have rarely been meaningful given the disparate ways in which the concept was operationalized, the EEI offers a measure of engagement standardized to a z-score scale. Subscales of the EEI measure all dimensions of engagement with equal weight and allow more granular comparisons of DBCIs. Using the EEI, engagement with DBCIs of varying designs can be compared more easily.

The Peterson and Carrabis and Taki et al. EIs were robust measures of engagement, but they did not operationalize the full engagement concept. This concept explication has identified deficiencies in the EI, particularly for assessing cognitive engagement. In addition, the below extensions of the EI enhance its ability to assess multiple facets of the behavioral engagement dimension, across all four phases.

1. An additional subscale should be added that, like the feedback scale, quantifies and standardizes indicators of Cognitive engagement from a population-based survey that gauges awareness and acceptability of the DBCI across the pool of potential users.
    a. Alternatively, if the DBCI is available to download in an app store, the number of downloads could be used as a numerator and the estimated population of potential users as the denominator to create a cognitive engagement (CEi) score.

CEi would be a constant across users for a DBCI at one point in time, assuming that it does not significantly vary across users.

2. The EEI should include subscales for feature-specific use (FSU) and feature breadth (FB). FSU should track whether the user reaches some threshold of 'adequate' engagement in specific features that are conceptually tied to psychosocial mechanisms of action in a theory-driven model of how the DBCI affects behavior change. FB should measure DBCI use across the full variety of DBCI features to understand the extent to which users are experiencing the full suite of messages and resources included in the DBCI.
3. EEI indicators should be collected over a defined study period that is explicitly reported alongside engagement results. In the Taki et al. study indicators were collected over a 9-month study period, however, the length of study should be dictated by the average length of use and extended by at least half in order to account for time to measure potential re-engagement with the DBCI.
4. Measures of each subscale should be collected in a time series to represent, where relevant, an initial period of engagement, an interim period, and the remaining time to complete the full study period. The cut-points for these times should be determined from the literature on length of use for similar DBCIs, cutting the average length of engagement in half to determine j1 and j2, and extending by at least half to set a j3 time point for the end of the study.
5. Rather than multiplying the sum of subscales by 100, as in the EI, the EEI standardizes the sum of the subscales to a z-score to help approximate a more normal distribution of EEI scores. This allows for a standardized scale with mean 0 for all interventions to which the EEI is applied, irrespective of whether all or a subset of the EEI subscales are employed. As the EEI may change over time, the standardization allows engagement distributions to continue to be comparable across interventions.

6. Remove the Brand subscale, which was included in the EI. The focus of this subscale better aligns with the concept of involvement than engagement, so it is not recommended to include it in the EEI.

Discussion

Engagement is a rich concept with multiple dimensions, several phases within the behavioral dimension, and numerous facets particularly when examining the period of engagement phase within behavioral engagement. Although cognitive and emotional engagement are important to measure in order to comprehensively assess a user's engagement with a DBCI, this review focused on behavioral engagement because the data exhaust from DBCIs provide a rich source for extracting insights about user engagement. In addition, data exhaust is an unobtrusive, passive data collection mechanism that is less prone to bias than self-report data and can be easily manipulated to calculate a variety of facets describing engagement.

By identifying a priority set of indicators that measure the various facets of engagement across phases of behavioral engagement, researchers can communicate clearly with intervention developers during the design process to describe their specific data needs for creating data exhaust tracking mechanisms. In addition, reflecting on a full suite of indicators for engagement during the design process can spark developers to consider the features they can embed to create more engaging interventions. For example, by considering the measure of recency developers may be prompted to incorporate cues to re-engage with the intervention to decrease participants' time lag between visits to the DBCI. Outlining indicators of engagement to track during DBCI development is optimal because it allows prospective data collection to analyze all of the facets of engagement that are of interest to the program and the larger research community. When engagement indicators are identified late in DBCI implementation, it is possible that the data exhaust will not have been captured or will be inadequate to measure the full concept of engagement. Rather than having the concept dictate the indicators for engagement, the available data would dictate its operationalization.

Operationalizing each phase of behavioral engagement provides valuable insight into the process of engagement. Point of engagement indicators reveal insights about initial usability and appeal of DBCIs. If few users reach thresholds for initial engagement with the DBCI this may indicate that there are barriers between DBCI discovery (the moment when participants become aware of the DBCI) and initial use. These barriers may relate to individual, social, or technology infrastructure influences on engagement. Alternatively, the DBCI may not have enough appeal to entice users to explore the intervention, and this may have implications for DBCI aesthetic redesign.

The crux of engagement operationalization lies in development of indicators to measure what is taking place as a user focuses her attention on the DBCI. As such, a comprehensive engagement metric should include several period of engagement indicators to assess length, breadth, depth and quality of engagement with the DBCI overall, and with specific features that the program theorizes will lead to psychosocial changes that predict behavior change. Overall DBCI period of engagement indicators help to determine whether the DBCI is a worthwhile investment for affecting health decision-making and behavior change, and feature-specific period of engagement metrics help evaluate how behavior change may occur. While some binary metrics that assess number of users reaching 'adequate' levels of engagement facets are useful descriptive statistics, continuous metrics for facets of the period of engagement can yield a much more rigorous evaluation of usage and its effect on outcomes.

Some of the most crucial indicators to include in DBCI evaluations are feature-specific depth of use indicators measured during the period of engagement. A single DBCI may include many features, so overall usage indicators are inadequate to understanding which features may be driving higher use and use of which features correlates most strongly with positive psychosocial and behavior change. Furthermore, when feature-specific depth of use indicators are tracked in a time series they can provide insight into shifting individual-level motivations driving sustained intervention use. Patterns of engagement may vary over time for subsets of users, and this may indicate motivations for DBCI use, and pathways for feature use that can keep users interested. Through these analyses a program can potentially enhance the effects of a DBCI on changing targeted behaviors by highlighting features that motivate and sustain engagement.

Re-engagement indicators are also important to build into an engagement metric. These indicators help to describe natural usage patterns with DBCIs particularly focused on health decisions and health changes. The saliency of a health-focused DBCIs may wax and wane throughout an individual's life. By tracking depth of engagement measures using a time series we are able to see the dynamic nature of engagement within discrete portions of a study period, rather than assuming engagement to be uniform throughout the period of engagement.

While studies have operationalized engagement in a wide variety of ways, synthesizing these indicators into facets, phases and dimensions helps to identify the commonalities of purpose across these engagement measures. Through this organizational structure, the EEI is able to clearly identify where past metrics of engagement are lacking in alignment with the full engagement concept.

Unit of measurement for behavioral engagement

It is important to define the population unit of interest for measuring engagement. Given that behavioral engagement focuses on the interaction between the user and the DBCI, a user is the unit of measurement for behavioral engagement indicators.

Users of DBCIs can be defined in a variety of ways: each visitor or user of an intervention, each registered user/user who logs onto the platform, each user who completes and initial assessment, or each user who returns beyond the initial visit. This preponderance of possible definitions underscores the imperative that studies of engagement clearly describe the unit of measurement in greater detail than 'user' of an intervention alone. This definition may help to further delineate point of engagement measures and measures of depth of engagement where users may be able to visit the DBCI with or without logging in and experience different types of content and features as a result.

Implications of the Extended Engagement Index

This review identified several strengths of the literature on engagement. Across a wide range of disciplines, there was consensus on the existence of three dimensions of engagement: cognitive, emotional and behavioral engagement. Operationalizations of engagement, though wide-ranging and often specific to the design of a particular DBCI, coalesced around a finite number of facets being measured. Operationalizations also ran the spectrum of phases of engagement, offering many possible ways to measure engagement as a process. This review found that studies triangulated on broad facets of importance to measure, particularly under the dimension of behavioral engagement.

The most obvious gap in the literature on engagement with DBCIs was a lack of robust measures of engagement that incorporated numerous indicators into a single scale. Indeed, only one scale – the EI – was identified, and it was only validated in a single intervention study. In addition, the EI did not align fully with the concept of engagement, lacking assessment of cognitive engagement and robust assessment of the facets of engagement included in other studies.

The EEI offers a robust measure that aligns with the full concept of engagement. The subscales the EEI also help to describe engagement in discrete ways, allowing flexibility to use the scales of relevance to a DBCI regardless of its design, and offering the ability to compare DBCIs based on the subscales that are commonly relevant. Finally, with the EEI being standardized to a z-score, engagement can be compared across EEIs even if the subscales included in the index differ for one DBCI to the next.

Limitations of the Extended Engagement Index

There are some limitations of this study. First, the conceptualization of engagement was informed by a small set of literature. It is possible that searching a wider range of databases, including ones related to marketing and social psychology may have yielded additional studies reflecting on this concept. Additionally, the operationalization of engagement relies mainly on analysis of data exhaust. While data exhaust is a rich source of data for complex interventions such as mobile applications, it may be a limited data source for simpler DBCIs such as push-only text messaging programs. In addition, the EEI does not assess how much a participant relies on the DBCI versus some other non-digital communication channel. Thus, it assumes that all psychosocial change that may occur during a study period can be attributed to engagement with the DBCI.

Planned use of Extended Engagement Index

There are many ways in which the EEI can be used in future research and DBCI program planning. Through analysis of engagement using the EEI DBCI programs can gain insight on how to refine their intervention strategies to improve engagement. Each subscale measures a different facet of engagement, and each facet of engagement can be linked to specific strategies for improving engagement. Programs can make informed decisions about the strategies they should incorporate in order to address low-performing facets of engagement. Rapid individual analysis of EEI built into program design could also help in tailoring DBCI content offered to participants. Based on a participant's choices and past actions using of the DBCI, promotion of frequently used features can be individually tailored to further sustain engagement.

It is reasonable to expect, and the goal of DBCI programs, that engagement may result in psychosocial effects that are mechanisms of action for changing a particular health behavior. As a result, a particular threshold of interest is 'adequate engagement.' By treating EEI scores as an independent variable, we can look at its correlation with psychosocial and behavioral outcomes that should be engagement-dependent. Through regression analyses we may look for spline terms or cut-points in the slope of the correlation between EI and dependent variables that could suggest what adequate engagement should be for a particular DBCI.

Regression analyses measuring the correlations between Interaction subscale scores and independent indicators within the subscale with psychosocial and behavioral outcomes could further help to determine thresholds for adequate feature-specific engagement. These analyses would be useful for DBCI program staff to help identify which DBCI features are being used to successfully affect mechanisms of action for behavior change, and which features may not be ideally suited to affect a mechanism. Features that are not ideally suited to affecting a mechanism of change may be replaced with an alternative communications tool or feature, and DBCIs addressing similar health topics and mechanisms of action can be compared to determine which out of a wide range of technology features are most successful for achieving a change on a particular mechanism of action.

In addition, EEI scores can be categorized for ease of interpretation (e.g., binary users vs. dropouts, or tertiles of high, medium and low engagement). Then, t-tests or ANOVA tests can be used to explore variation in demographic profiles and patterns of feature use across levels of engagement.

Conclusions

The field of digital health needs more consistency in how it conceptualizes and operationalizes the phenomenon of engagement with DBCIs. To better match the multi-faceted concept, summary indicators of engagement should encompass all three dimensions of engagement, the four phases of behavioral engagement and multiple facets of engagement over those phases. The EEI is a comprehensive measure, flexible to accommodate a variety of DBCI designs but also standardized into scores. The EEI can serve as a powerful tool for comprehensively evaluating engagement with DBCIs and comparing engagement across DBCIs that address similar health topics and psychosocial change processes.

Table 3.1: Databases, search strategies, eligible documents and elimination criteria applied

Search database	Search strategy	Overview
PubMed	**Search terms included:** • Digital health and related keywords (e.g., telemedicine, digital health, mHealth, etc) • Health AND Decision-support • Engagement and related keywords (e.g., patient engagement, customer engagement, etc.)	• **Eligible: 62 / 1,179** • Eliminated: 1,117/1,179 o Did not support relevant stages of health decision-making and behavior change: 419 o No substantive focus on digital engagement: 300 o No metric applied to Intervention: 57 o Not customer facing: 207 o Clinical: 134
CMMC Communication and Mass Media Complete	**Search terms included:** • Digital health and related terms (e.g., telemedicine, digital health, moble health, etc) • Health AND Decision-support • Engagement and related terms (e.g., patient engagement, customer engagement, etc.)	• **Eligible: 0 / 48** • Eliminated: 48/48 o No substantive focus on digital engagement: 30 o Did not support relevant stages of health decision-making and behavior change: 11 o Not customer facing: 2 o Clinical: 2 o No metric applied to intervention: 3
HCI Database Human-Computer Interaction Database	**Search terms included:** • Mobile phones and related terms (e.g., phone, device, computer) • Health and related terms (e.g., health, healthcare, doctor) • Engage	• **Eligible: 0 / 60** • Eliminated: 60/60 o No substantive focus on digital engagement: 36 o Did not support relevant stages of health decision-making and behavior change: 13 o Clinical: 7 o Not customer facing: 4 o
Grey literature, reviews of references, & referrals by subject experts	N/A	• **Eligible: 7/12** • Eliminated: 5/12 o Did not support relevant stages of health decision-making and behavior change: 4 o Clinical: 1

Table 3.2: Examples of quantitative and qualitative indicators measuring cognitive and emotional engagement

Dimension of engagement	Type of measure	Use indicator	Data source	Studies
Cognitive	Qualitative	Discussion of when DBCI was used	Interviews with users	Morrison et al 2014
Cognitive, Emotional	Qualitative	Discussion of acceptability and satisfaction with DBCI for self-monitoring	Focus group discussions	Tatara et al. 2013
Emotional	Continuous	Satisfaction with DBCI overall, willingness to recommend DBCI overall	Close-ended survey	Quintilliani et al. 2016
Emotional	Continuous	Engagement Index feedback subscale	Close-ended survey	Taki et al. 2017
Emotional	Qualitative	Perception of each program component	Semi-structured telephone interviews with subset of users	Partridge et al. 2016

Table 3.3: Quantitative and Qualitative indicators measuring behavioral engagement – Point of engagement

Type of measure –DBCI overall or by feature	Use indicators	Data source	Facet of engagement phase	Studies
Binary – overall	Opened the intervention, Logged into intervention at least once, Completed 2-step enrollment process to be "fully enrolled"	Data exhaust	How many reached initial engagement	Mattila et al. 2013, Nash et al. 2015, Estrada et al 2017, Buis et al. 2013
Binary – feature-specific	Used specific feature at least once (binary measure for each feature), Viewed at least one electronic guide related to the intervention, Made at least one self-monitoring entry, Consulted any advice, Wrote a textual description for first self-monitoring photo uploaded	Data exhaust	How many reached initial feature-specific engagement	Nash et al. 2015, Penchman et al. 2015, Buis et al. 2013, Glasgow et al. 2007, Mattila et al. 2013, Dennison et al. 2014, Helander et al. 2014, van Drongelen et al. 2016, Wiener et al. 2016
Continuous – overall	Days elapsed from baseline assessment to first visit	Comparing baseline database with Data exhaust	How long takes to get initial engagement	Danaher et al. 2006

Table 3.4: Quantitative and Qualitative indicators measuring behavioral engagement – Period of engagement

Type of measure – DBCI overall or by feature	Use indicators	Facets of engagement phase	Studies
Binary - overall	Remained subscriber for whole intervention period (did not un-enroll)	How many achieved threshold of engagement	Heminger et al. 2016
	Retuned once after initial login	How many achieved *low* threshold of engagement	Nash et al. 2015
	Used DBCI daily, for whole study period	How many achieved *high* threshold of engagement	Nijland et al. 2011, Mattila et al.2013, Scherer et al. 2017
Binary – feature-specific	Used specific feature at least threshold number of times: Viewed at least one follow-up newsletter, Replied to a specific text prompt, Uploaded 2+ self-monitoring pictures and thus classified as "User"	How many achieved *low* threshold of engagement	Glasgow et al. 2007, Heminger et al. 2016, Helander et al. 2014
	Completed "core modules"/used core features of DBCI/completed majority of curriculum	How many achieved *"adequate"* threshold of engagement	Dennison et al. 2014, Zeng et al. 2016, Wilson et al. 2017
	Logged into DBCI at least once per week, consulted advice for at least 4 weeks	How many sustained *"adequate"* threshold of engagement	Fontil et al. 2016, van Drongelen et al. 2016
	"Complete adherence" to a feature defined as: Used self-monitoring feature daily, Completed all modules	How many achieved *high* threshold of engagement	Shapiro et al. 2010, Estrada et al. 2017, Buis et al. 2013, Staffileno et al. 2015
	Used 2 or more communication channels within DBCI	How many achieved threshold breadth of engagement	Owen et al. 2016

Continuous – overall	Days elapsed from first to last visit (within a study period)	Length of engagement	Du et al. 2016, Serrano et al. 2017, Buis et al. 2013, Kim et al. 2016
	Total number of visits (per user) within study period, Total number of logins (per user) within study period	Length of engagement, Depth of engagement	Danaher et al. 2006, Richardson et al 2013, Kuijpers et al. 2016, Bush et al. 2017, Scherer et al. 2017, Anderson et al. 2016, Glasgow et al. 2011, Partridge et al. 2016, Serrano et al 2017, Moin et al. 2015, Short et al. 2017, Heminger et al. 2016
	Number of features used, Number of pages of site accessed, Number or messages listened to for SMS-based DBCI	Breadth of engagement	Partridge et al. 2016*, Danaher et al 2015, Zeng et al. 2015, Richardson et al 2013, Stellefson et al. 2013, LeFevre et al. 2017
	Number of components used at least twice	Breadth of *"adequate"* engagement	Glasgow et al. 2011
	Number of workflow data captures/ decision made out of total in DBCI	Breadth and depth of engagement	Danaher et al. 2015
	Total duration of visits (per user)	Depth of engagement	Danaher et al. 2006, Richardson et al 2013, LeBlanc et al. 2015, Glasgow et al. 2011, Owen et al. 2016, Short et al. 2017
	Average duration per visit (per user)	Depth of engagement	Danaher et al. 2006, Puszkiewicz et al. 2016**, Anderson et al. 2016
	Engagement Index subscales for click depth, loyalty, interaction within study period	Length, depth, and feature-specific depth, Dynamic nature of engagement	Taki et al. 2017

Continuous-topic specific	Number of pages viewed by topic	Depth of engagement in topic	Danaher et al. 2015
	Number of days per week used tracking function by topic	Depth of engagement in feature AND topic	Tatara et al. 2013
Continuous-feature specific	Time spent viewing specific web pages (per user)	Length of feature-specific engagement	Danaher et al. 2006, Brusk & Bensley 2016, Owen et al. 2016
	Number of times visiting/viewing a specific feature: quit plan, skill practice, testimonials, external links, personal health data, appointment calendar, Number of messages listened to	Depth of feature-specific engagement - *passive*	Hales, Davidson & Turner-McGrievy 2014, Partidge et al. 2016, Heffner et al. 2015, Brusk & Bensley 2016, Kuijpers et al. 2016, Lin et al. 2015, LeFevre et al. 2017
	Number of actions per page or feature: For example posts/ status updates/comments/poll votes, uploads, likes, tracking progress of letting urges pass, making quit or action plans, setting behavioral goals, recording self-monitoring data, attending synchronous meetings, making a call or sending a message for counseling***, sending private message***	Depth of feature-specific engagement - *active*	Danaher et al. 2006, Stellefson et al. 2013, Turner-McGrievy & Tate 2014, Moin et al. 2015, Padman et al. 2013, Turner-McGrievy & Tate 2013, Penchamn et al. 2015, Wang et al. 2016, Merchant et al. 2014, Tague et al. 2014, Glasgow et al. 2011, Heffner et al. 2015, Moin et al. 2015, Short et al. 2017, Ehlers, Huberty & deVreede 2015, Stellefson et al. 2013, Mamykina et al. 2016, Goode et al. 2015, Christofferson et al. 2016, Goyal et al. 2017, Quiltilliani et al. 2016
	Number of people with whom user communicates***	Depth of feature-specific engagement - *active*	Owen et al. 2016
	Progress toward 'complete' engagement: Percent of sessions/modules completed, Reply rate to SMS/emails/	Depth of feature-specific engagement	Dennison et al. 2014, Danaher et al. 2015. Turner-McGrievy & Tate 2014, Moin et al. 2015,

	coaching calls (per user)		Goyal et al. 2016, Short et al. 2017, Kornman et al. 2010, Partridge et al. 2016, Lin et al. 2015, Grutzmacher et al. 2017, Scherer et al. 2017, Quiltilliani et al. 2016
	Frequency reaching a threshold of taking an action per feature: Number of days self-monitor at least once, Number of weeks replied to at least 3 messages	Depth of *"adequate"* feature-specific engagement - *active*	Kato-Lin et al. 2015, Glasgow et al. 2011, Capozza et al. 2015
	Number of characters in a reply message, Response time to reply to a message***	Emotional quality of engagement	Kornman et al. 2010
Qualitative – feature specific	Qualities of active use of feature: SMS responses/social media posts: relevant to intervention prompt, spontaneous unprompted by DCBI post)***	Achieve a threshold of engagement quality	Kornman et al. 2010, Penchman et al. 2015
	Qualities of SMS responses: Use of shorthand/emoticons in SMS response***	Emotional quality of engagement	Kornman et al. 2010
Qualitative collection, quantified – feature specific	Report "lurking" on social media pages (visiting but not making comments)[t]	Descriptive statistic for depth of engagement - *passive*	Merchant et al. 2014

*In Partridge et al. 2016 the data source was online surveys with self-report
** In Puszkiewicz et al. 2016 the data source was self-report
*** Data source is database of messages or responses sent/calls made/posts made
[t] Data source is interviews with a representative subset of users

Table 3.5: Quantitative indicators measuring behavioral engagement – Disengagement and Re-engagement

Phase of engagement	Type of measure – DBCI overall or by feature	Use indicators	Data source	Facets of engagement phase	Studies
Disengagement	Binary - overall	Dropped out of intervention prior to completing all sessions/end of intervention period	Data exhaust	How many DID NOT achieve "adequate" threshold of engagement	Lie et al 2017, Buis et al. 2013, Mitchell & Faulkner 2014, Chaplais et al. 2015, Coa & Patrick 2016, Goldstein et al. 2017
Re-engagement	Continuous in a time series - overall	Number of visits over discrete time periods within the study period: Number of visits per day (per user), Number of visits/logins per week Number of visits per week splitting first half of intervention period vs. second half of intervention period	Data exhaust Self-report by Puszkiewicz et al. 2016	Dynamic nature of engagement	Danaher et al. 2006, Mamykina et al. 2016, Milani et al. 2017, Kim et al. 2016, Muuraiskangas et al. 2016, Puszkiewicz et al. 2016, Scherer et al. 2017, Glasgow et al. 2011
	Continuous, averaged in a time series - overall	Engagement index subscale for recency within study period	Registration database and Data exhaust	Dynamic nature of engagement	Taki et al. 2017

Table 3.6. Subscales of Engagement Index (Taki et al. 2017)
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Sub-scale	Formula	Calculation period, Data source	Final calculation	Meaning*
Click Depth (CDi)	$\frac{\text{Sessions having "at least 2 pages viewed"}}{\text{All sessions}}$	Initial: j1 = 0-3 months Interim j2 = 3-6 months Final j3= 6-9 months Source: Data exhaust	$=\sum_{j=1}^{n}$ (Subscale/n)	Behavioral engagement – Period of engagement, Depth of engagement
Loyalty (Li)	$1-\left(\frac{1}{\text{Number of sessions accessed during the timeframe of the program}}\right)$			Behavioral engagement – Point through Period of engagement to Disengagement, Length and frequency of engagement
Interaction (Ii)	$\frac{\text{Number of push notifications opened}}{\text{Total number of push notifications sent}}$			Behavioral engagement – Period of engagement, Feature-specific depth of engagement
Recency (Ri)	$\frac{1}{\text{Average number of days between visits for each period}}$	j1 = days between registration and initial DBCI visit j2 = 3-6 months j3= 6-9 months Source: Data exhaust		Behavioral engagement – Point of engagement at j1, Re-engagement & Dynamic nature of engagement at j2 and j3

Feedback (Fi)	$\frac{\textit{Number of positive responses}}{\textit{All quantitative questions asked about their satisfaction with the Growing healthy app}}$	Endline – 9 months Source: Close-ended user survey with 37 questions		Emotional engagement – Satisfaction, usability, perceived quality and willingness to recommend

Note: In these formulas i=ith person, j=jth time period over 9-month study, and n=3 for CDi, Li, Ii and Ri (sum of calculation period) and n=37 for Fi. An overall score on the engagement index is calculated as: EI score = (Sum of CDi+Li+Ii+Ri+Fi)*100
*Meaning pertains to the dimension of engagement concept, phase of engagement where relevant, and facets of engagement.

Figure 3.1: Number of Pubmed publications fitting search term for engagement in DBCIs, by year

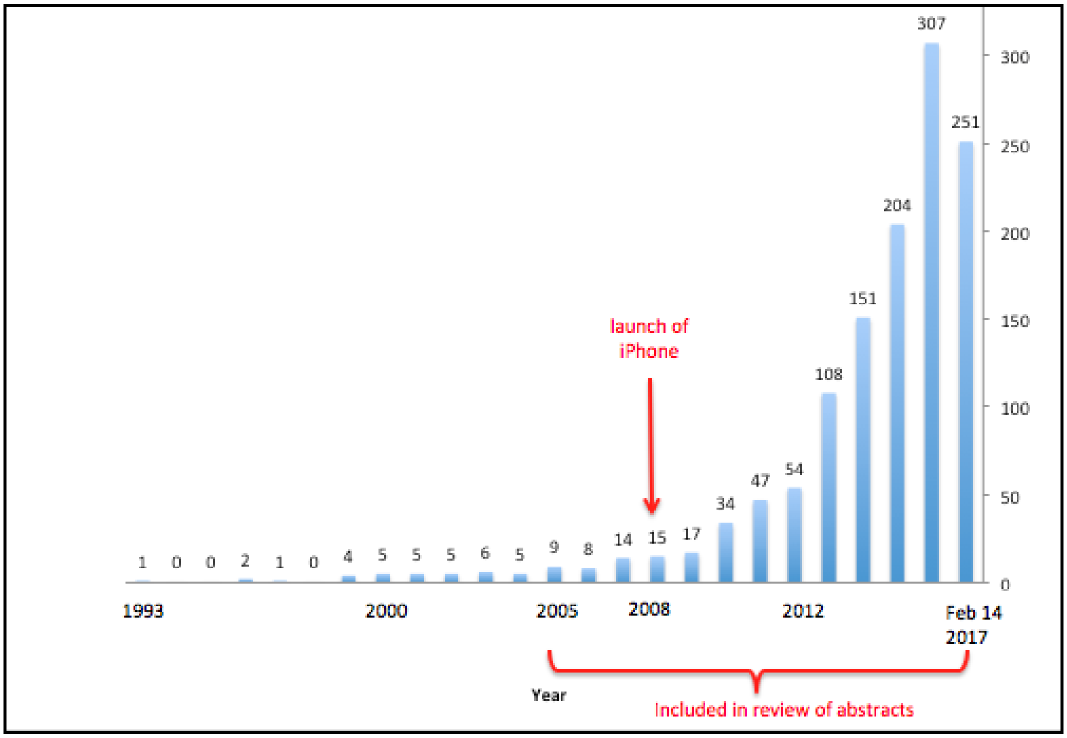


Figure 3.2: Flow diagram of search strategy to identify studies for review of operationalizations of engagement with DBCIs

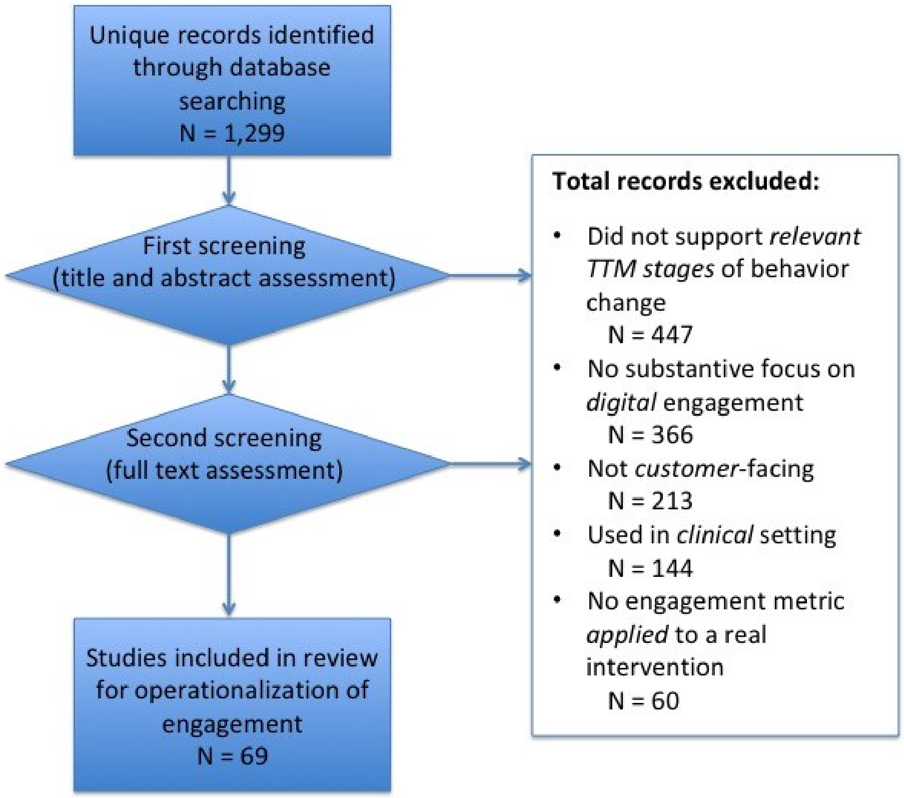


Figure 3.3: Summary of the number of studies identified to describe operationalization of engagement with DBCIs across three dimensions, and four phases within the dimension of behavioral engagement

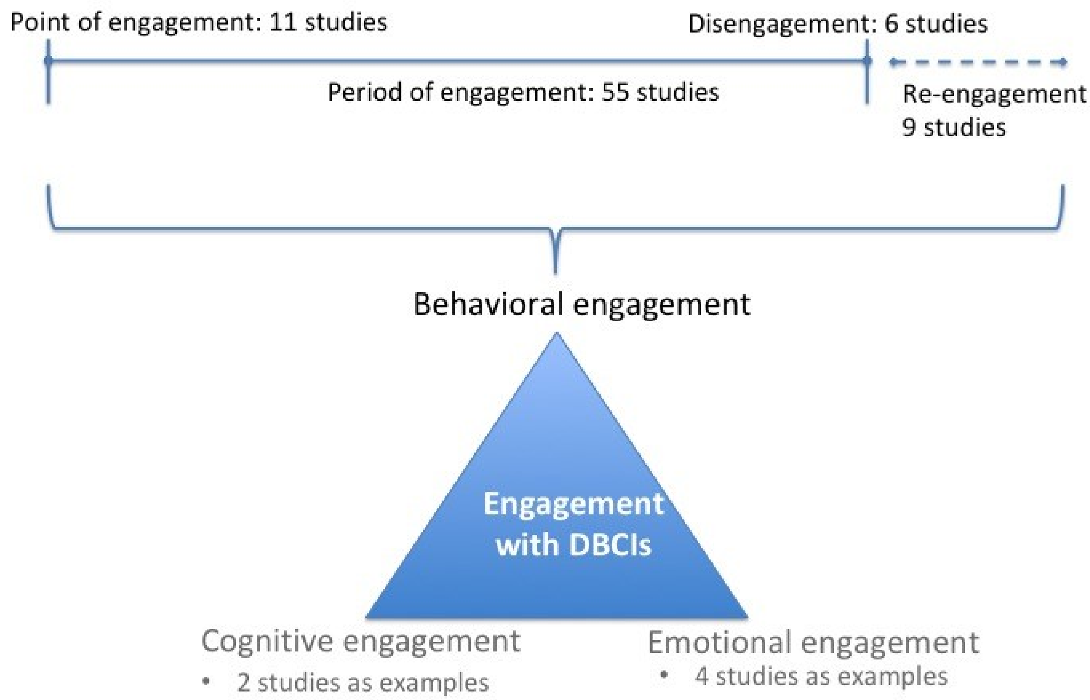
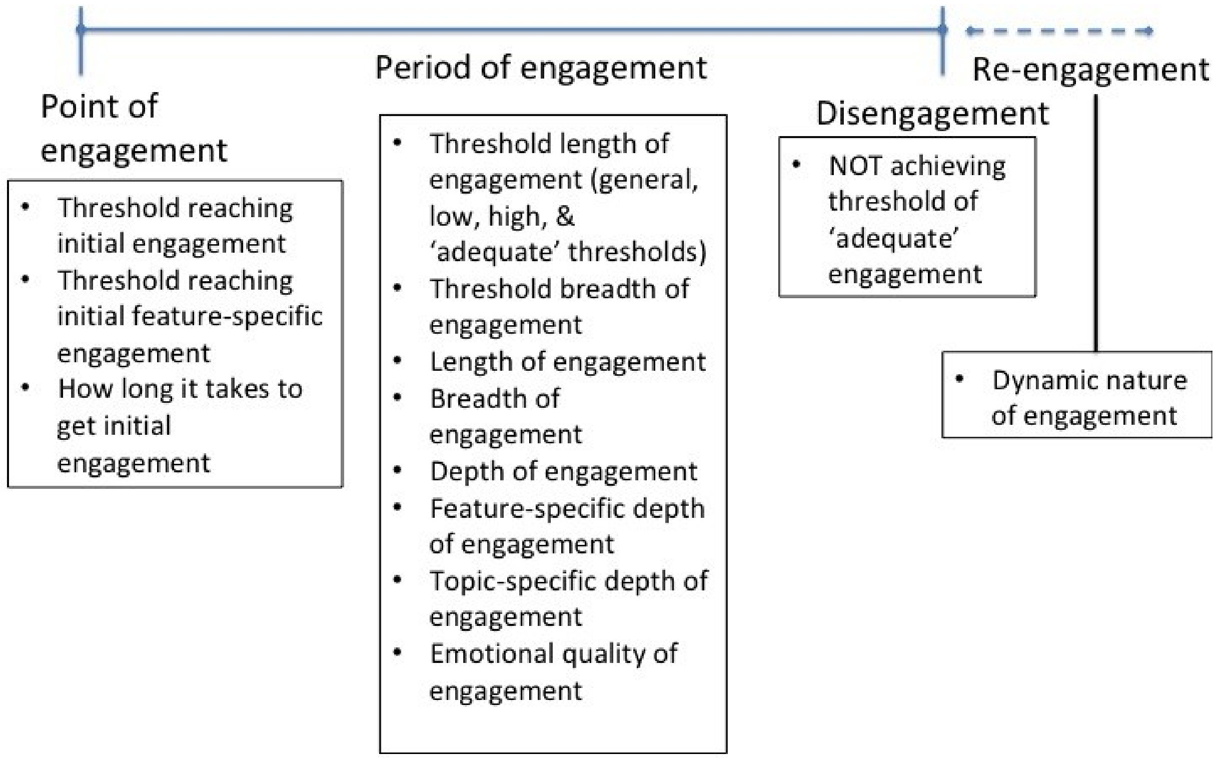


Figure 3.4: Summary of the facets of behavioral engagement identified at each phase of engagement with DBCIs



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Chapter 4: Predictors of engagement with the Skata mobile application for family planning in Indonesia: Application of the Extended Engagement Index

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Chapter 4 – Predictors of engagement with the Skata mobile application for family planning in Indonesia: Application of the Extended Engagement Index

Abstract

Indonesia has a long history of family planning success; however, the uptake of modern contraceptives has stalled over the past decade. The Skata mobile application was designed to integrate into a user's lifestyle, helping couples plan their lives together, including determining fertility goals and making contraceptive method choices that align with their goals. To understand long-term appeal of Skata app, this study explored factors predicting engagement with the mobile application. The study applied the Extended Engagement Index (EEI) to Skata app and website usage data collected from April – August 2016. The study assessed the scale's reliability and tested its validity against a typical measure of engagement, length of use. The EEI was also utilized as an outcome to assess factors that predicted engagement in Skata. Data were restricted to adult male and female users who registered with Skata and visited Skata at least once (n=15,909). An EEI score was calculated for each user using six subscales: click depth, duration, loyalty, interaction, recency, and feature breadth. The score was calculated using three time periods: the first visit, visits 2-3, and visits 4 and beyond.

Similar results were obtained comparing demographic and Skata access features over a dichotomized Z-score standardized EEI score and a dichotomized length of use measure. Specifically, more engaged users were more likely to be female, newly married under age 35 or spacing or limiting children, and access Skata through the app only or a combination of the app and website. Compared to length of use, the distribution of the standardized EEI score more closely approximated a normal distribution and had strong internal consistency (Chronbach's Alpha = .8630). Using an exploratory factor analysis on Skata page use in visits 2 and beyond, five factors were identified, representing motivational patterns underlying Skata use. The motivational factors were: 1) contraceptive decision-making, 2) scanning with a focus on child

education, 3) scanning with a focus on contraception, 4) scanning and planning, and 5) time management. Regression analyses identified demographic, Skata access, and psychographic factors that predicted Skata engagement defined as Z-score standardized EEI scores. A final multivariate regression model concluded that users were significantly more engaged with Skata if they were under age 35 and spacing children or were limiting childbearing, and if they were motivated to use Skata for any of the four factors related to seeking and scanning motivations. Users were significantly less engaged with Skata if they only accessed Skata through the website.

The methods of this study illuminate ways in which programs can better understand who comprise their most engaged audience(s) and what features of the intervention are driving engagement. The findings of this study can assist developers of family planning digital applications develop interventions that sustain user interest.

Introduction

Indonesia has a long history of family planning (FP) success, however, the uptake of modern contraceptives has stalled for over a decade. Specifically, the modern contraceptive prevalence rate (mCPR) was recorded at 57.2% in 2017 and 56.7% in 2003 (DHS Indonesia 2017). Furthermore, the FP method-mix has shifted towards heavy use of short-term methods such as injectables and oral contraceptives over the last 20 years, with 32% and 14% of married FP-using women ages 15-49 using injectables and oral contraceptives in 2012 compared to 12% and 15%, respectively in 1991 (DHS Indonesia 2012). These methods are popular and effective in the short term, but more difficult to use consistently and therefore less reliable for longer spacing of births or after a couple has achieved their desired family size. Long-acting reversible contraceptives (LARCs), such as intra-uterine devices (IUDs) and implants, are more reliable for long-term spacing and limiting of births, but use has fallen from 13% and 3%, respectively in 1991 to 4% and 3% in 2012 (DHS Indonesia 2012). In this context, the Johns Hopkins Center for Communication Programs, supported by the Bill and Melinda Gates Foundation, launched a suite of FP demand generation activities to reinvigorate the national FP program in Indonesia. One piece of the demand generation work was development and implementation of a mobile application (app), called Skata, to help develop more informed FP consumers.

The Skata app was designed to integrate into user's lifestyle, helping them to plan their lives, including their fertility goals, and assisting users in making FP choices that align with their goals. Skata was developed by a Jakarta-based digital production agency and launched nationally in April 2015. It was available for download through the Google Play and iOS App stores, as well as through a mobile-optimized website, www.skata.info. Skata provided tools for planning one's family, as well as detailed information about modern contraceptive methods, with an emphasis on the advantages of LARCs for effective spacing and limiting of pregnancies. In addition, Skata had a GPS-enabled feature that helped users locate nearby providers of FP services. Skata also included articles, checklists and planners that were intended for routine use, so that the app would have long-term appeal to users even between moments when they were involved in making an FP decision.

To understand long-term appeal of the app, we refer to the literature on engagement. Engagement has been defined as a dynamic, interactive and iterative process where an individual plays an active and meaningful role in planning and decision-making for health services that affect their lives (Gallivan et al. 2012). Applied to digital interventions, the Engagement Index (EI) by Petersen and Carrabis 2008 and adapted by Taki et al. in 2017, operationalized this concept by measuring seven facets of interactions between a user and a digital intervention: click depth, loyalty, interaction, recency, feedback, duration and brand. Earlier in this thesis I extended the Engagement Index to include subscales for cognitive engagement, feature-specific engagement and feature breadth, and to follow recommendations for data collection over a time series. With these additions the Extended Engagement Index (EEI) comprehensively measures the engagement concept.

Predictors of engagement have also been explored in several studies. Individual-level predictors of engagement include demographic factors and psychographic motivations for use. Demographic factors such as age and gender have been associated with engagement in digital behavior change interventions (DBCIs) (Ben-Zeev et al 2016, Kontos et al. 2014, Glasgow at al. 2007, Nash et al. 2015). In addition, psychographic factors, such as baseline autonomous motivation, have been correlated with engagement (Coa and Patrick 2016), as has use of self-monitoring and other efficacy-building intervention features (Glasgow et al. 2011, Glasgow et al. 2010).

To date, there has been little study of engagement in the context of FP DBCIs, and no study has explored this outcome for DBCIs specifically in Indonesia. Understanding predictors of engagement with a FP DBCI can be instructive to other digital FP demand generation programs, and the Indonesian context may be similar to other developing countries in which the mobile infrastructure is growing at a rapid pace. Few studies have robustly measured engagement, and none have yet applied the EEI.

Study Objectives

The objectives of this study were to:

1) Apply the EEI to data from a real DBCI, such as the Skata mobile app and website;
2) Assess the reliability and validity of the EEI against a more traditional engagement measure, such as length of use;
3) Identify patterns underlying the use of the Skata mobile app/website; and to
4) Determine if there are correlations between patterns of use and overall engagement with the Skata app/website.

Methods

Data collection

The data for this study came from the data exhaust, or tracked usage data, from the Skata mobile app and website. The lead researcher worked with the program team and app developers to determine a framework for tracking app and website use. Users could register with Skata, either via Facebook or with their own email address and password, in order to get access to the full suite of features offered in the app. Users who registered were assigned a unique identification number (ID) and asked a series of demographic questions. These demographic data along with the registered user's app use was tracked through a real-time dashboard. The dashboard recorded a timestamp and actions taken of accessing or posting data per each of 41 designated page types within the app. Some tracked pages were nested under others, and a full list and description of tracked pages is available in Table 4.1.

This study used data exhaust from April – August 2016. This period represented the initial five months following Skata's official launch through mass media promotion in 11 selected districts of Indonesia. Users who registered during this time period and had at least one potential month of use were included in the study (e.g., registered April 1 – Aug 1, 2016). A total of 17,047 adult users registered with Skata during that time, of which 15,909 visited at least one page within the app (93.32%) and were thus tracked through the data exhaust and eligible for this study.

Development of the outcome indicator

This study compared two potential outcome indicators for engagement: a dichotomized length of use variable and a dichotomized extended engagement index variable standardized to a z-score. Engagement has been operationalized in a multitude of ways including percentage continuing to be a subscriber/user for the full length of study (Heminger et al. 2016), number of

DBCI features used in the study period (Partridge et al. 2016), and average duration per visit (Danaher et al. 2006, Puszkiewicz et al. 2016, Anderson et al. 2016). However, the most common indicator of engagement is number of visits or length of intervention use in days over the study period (Du et al. 2016, Serrano et al. 2017, Buis et al. 2013, Kim et al. 2016, Danaher et al. 2006, Richardson et al 2013, Kuijpers et al. 2016, Bush et al. 2017, Scherer et al. 2017, Anderson et al. 2016, Glasgow et al. 2011, Partridge et al. 2016, Moin et al. 2015, Short et al. 2017, Heminger et al. 2016). In this study the mean length of use was 12.65 days, ranging from 1 – 149 days, for the full study period. So, one month of use was the cut-off point for dichotomization to create two distinct user groups of reasonable size for comparison. Length of use was calculated as the number of days that elapsed from the first visit to the last recorded visit in the study period.

In addition to length of use, this study operationalized the Extended Engagement Index (EEI) (See Chapter 3) and used the index as a basis for creating a robust engagement outcome variable. The EEI is based on the Engagement Index (EI) (Petersen and Carrabis 2008), a scale developed by experts in the field of digital analytics, who assessed the indicators for face validity to ensure that they seemed to measure engagement through the use of data exhaust. A modified version of the scale has been validated in at least one study (Taki et al 2017), but uptake of the scale has been limited to date. In Chapter 3 of this thesis, the content explication further assessed the EI for content validity, resulting in extensions of the scale to ensure that the range of meanings of engagement were being measured within the index. This study, by comparing the EEI against the days of use measure of engagement, assesses criterion validity of the EEI to determine whether dichotomized versions of each indicator result in similar findings about individual characteristics that correlate with higher levels of engagement. Convergent and discriminant construct validity of the full EEI was not assessed in this study, however we explored correlations between subscales in the EEI to ensure internal consistency.

Based on the data available from the Skata app, six subscales of the EEI were used in this study. They were: click depth, duration, loyalty, recency, interaction and feature breadth. The feedback subscale was not included because these analyses were conducted on secondary data where it was not possible to survey the users during the study period to ascertain their feedback about satisfaction with Skata. The cognitive engagement subscale was not included because, based on the available data of number of downloads during the study period out of potential users in the target area, the data would be constant for all users in the study. The cognitive engagement subscale is most meaningful when comparing engagement across similar interventions, so it was not used here to understand predictors of engagement in a single intervention. The feature-specific use subscale of the EEI was excluded in this study because it did not enhance the internal consistency of the scale once operationalized. Each of the six included subscales was calculated using data exhaust, according to formulas proposed in the EEI, over three time periods: the first visit, visits 2 to 3, and visits 4 and beyond (see Appendix 6). These time periods were chosen to reflect logical breaks in the drop-off of users, with 53.45% of Skata users dropping off after one visit, 30.75% of users dropping off at either visit 2 or 3, and the remaining 15.80% of users visiting Skata 4 times or more. Subscale scores for all time periods were summed and divided by the number of time periods measured to create six subscale scores ranging from 0-1, or a full EEI measure that could range from 0-6. While most subscales were measured using the total sample of users who ever accessed Skata (n=15,909), the duration subscale was calculated with a smaller sample that excluded users who dropped off after accessing the first page of Skata on their first and only visit (n=15,461).

The EEI measure was manipulated to make it more suitable for further analysis. First, EEI scores were standardized so that the distribution better approximated a normal distribution. Standardized EEI had a mean -.004 and standard deviation of .773. To make the standardized EEI measure comparable to dichotomized length of use, standardized EEI was dichotomized at its mean to create low engagement and high engagement groups of registered Skata users.

Analytical procedures

Exploratory analyses of the Skata users' demographics and app/website usage were conducted. We compared Skata users who had used the app/website for less than one month to those who used it for one month or longer, and we compared Skata users with low and high engagement based on the standardized EEI. Variance ratio tests were conducted to identify unequal variance between the two groups being compared for each of these two outcome variables, and two-sample t-tests with unequal variance were done to assess any significant differences in means while two-proportion z-tests were used to assess differences in proportions across the groups for each outcome indicator. Through these analyses as well as an examination of the two indicators' distributions, a single indicator was selected to be the outcome utilized in subsequent analyses in this study.

An exploratory factor analysis (EFA) was used to determine any underlying patterns within the Skata app/website usage data. The mean number of visits to a page type were only slightly higher during visit 1 compared to visits 2-3 and lower than visits 4+, as shown in Table 4.2. The high standards of deviation for mean visits per page, particularly in visits 4+, indicated users may have used Skata for a variety of purposes and thus exhibited different use patterns, suggesting that users were a non-homogenous group. The average breadth of features accessed in visit 1 was much greater than in subsequent visits with higher standard deviations, thus patterns of use were more clearly defined in visits 2 and beyond. As a result, usage data from visit 1 was excluded from this analysis. The EFA was conducted with iterated principal factors to improve communality estimates. Factors were retained based on examination of a screeplot for the principal components and a parallel analysis of the factors. The factor solution was rotated on an orthogonal axis where correlation of factors was set to 0 to increase the interpretability of factor loadings. App/webpage types that loaded onto a factor at .4 or greater were considered to be measures contributing to the factor, and no app/webpage was allowed to contribute to more than one factor. Scores were calculated for the retained factors.

The final analytical step in this study was a series of regression analyses to explore the relationship between demographic characteristics, app access characteristics and motivations for app use as characterized by retained factors from the EFA on predicting standardized EEI scores. Each independent variable was regressed on standardized EEI scores using a simple linear regression. Several interactions between variables were tested to explore potential modification of relationships between predictor variables and the outcome. Afterwards a full multivariate linear regression model was developed incorporating all independent variables that showed statistically significant univariate linear relationships with the outcome. Multicollinearity of the variables was tested using variance inflation factors (VIF), and variables with a VIF greater than 10 were eliminated from the full multivariate model. Finally, an optimal multivariate model was developed to include non-collinear statistically significant univariate predictors of engagement.

Results

Demographics of sample

A total of 15,909 people registered as Skata users and accessed at least one page of the app during the period from April 1 – Aug 1, 2016. Demographic data and app/website access characteristics for the sample can be found in Table 4.3. While the majority of registered Skata users completed a series of questions to provide basic demographic data, sizeable proportions of users did not provide information such as age (37%), gender (14%), or information about their history of childbearing and fertility goals in order to determine their life stage (34%). The largest proportion of users were ages 18-34 (60%) and female (69%). While few Skata users reported being unmarried (5%), newlyweds who were married but had no children comprised 18% of all registered users, spacers who had at least one child and intended to have more children comprised 36% of the sample, and limiters comprised 7%. Registered users used Skata for an average of

12.7 days and visited the app/website an average of 2.3 times. Most users logged into Skata using their Facebook identity and password (63%) and accessed Skata using the mobile app (80%).

The full sample of 15,909 registered and tracked Skata users were compared using two different dichotomized metrics: length of use and standardized EEI scores. Registered users who used Skata for one month or longer were significantly less likely than shorter-length users to have unavailable age, gender or life stage data (19% vs. 40%, $p<.001$; 7% vs. 15%, $p<.001$; and 14% vs. 37%, $p<.001$, respectively). Month or longer users were significantly more likely than shorter-term users to be categorized in a life stage, with significantly more longer length users across nearly every life stage from young newlyweds under age 35 (17% vs. 15%, $p<.01$) to spacers (49% vs. 34% $p<.001$) and limiters (11% vs. 6%, $p<.001$). When comparing high engagement to low engagement users as determined by standardized EEI scores, the pattern of demographic results was similar.

Length of Skata usage, by definition, varied significantly by engagement group. Skata users who were engaged for one month or longer used the app/website for an average of 73 days (sd=32.50) and made an average of 6 visits in that time (sd=4.51). When standardized EEI was used as an outcome, because the distribution of this variable was more normal and the variable was dichotomized at its mean, the average length of use and number of visits differed from results for month or longer users. High engagement participants used Skata for 27 days on average (sd=36.13) and made an average of 4 visits (sd=3.18) during that time. Similarly, we found significant differences ($p<.001$) when comparing mean standardized EEI scores across length of use and standardized EEI categories.

Some app access characteristics varied by engagement level. There was no significant difference in login method between month-long and shorter length users and significant but qualitatively minor differences between high and low engagement users (64% vs. 61% logged in via facebook, respectively, $p<.001$). However, the platform through which users accessed Skata was correlated with engagement. Both month-long and high engagement users were more likely than their lower engaged counterparts to use the app only to access Skata (97% vs. 78% and 95% vs. 70% respectively, both $p<.001$) or to use a combination of app and website (0.76% vs. 0.19% and 0.56% vs. 0.05% respectively, both $p<.001$).

Outcome variable comparison and selection

Descriptive results for continuous days of use and standardized EEI scores were compared to determine whether the more robust standardized EEI variable could be an adequate replacement for the simpler length of use engagement outcome variable. A visual inspection comparison of the distribution of each variable revealed that the standardized EEI score was more normally distributed (see Figures 4.1-4.2). In addition, the distribution of standardized EEI scores was less skewed and had lower kurtosis than the days of use distribution (.624 and 2.456 vs. 2.733 and 10.1116, respectively). The multi-modal standardized EEI distribution further suggested that Skata users are non-homogenous, with at least two groups: a less engaged and a more engaged group of users.

The standardized EEI scale is comprised of six subscales: click depth, duration, loyalty, recency, interaction and feature breadth. This comprehensive scale accounts for more aspects of engagement than length of use alone. Most subscales within the EEI were statistically significantly correlated with one another (range from .2991 to .7803, $p<.001$ for all correlations) and the overall scale had moderately high internal validity (Chronbach's alpha = .8630) (Table 4.4). Each subscale of the EEI revealed significant differences in its respective aspect of engagement when compared across groups for the outcomes length of use and EEI score (Table 4.5). Specifically, one month and longer users exhibited significantly more click depth, longer duration, greater loyalty, interaction, recency, and feature breadth than shorter-length users at $p<.001$. High engagement users showed similar patterns across the subscales when compared to low engagement users, at $p<.001$. While most subscale scores were calculated using the full sample of registered users who had visited at least one page of Skata (n=15,909) the duration subscale used a total sample size n=15,461 reflecting 448 users who dropped off after accessing a single page of Skata on their first and only visit to the app/website. This phenomenon is called "bounce rate" and indicates a 2.82% bounce rate for Skata users with at least one month of potential app use who registered with the app during the period from April-August, 2016. Duration sample sizes were thus n=13,250 for less than one month of use, n=2,211 for one month or more use, n=8,777 for low engagement and n=6,684 for high engagement.

The standardized EEI variable draws from a richer set of data than the more traditional length of use variable when representing engagement outcomes. Based on the distribution characteristics, internal validity of the scale, and consistency of its findings with the days of use outcome, we elected to use standardized EEI score as the outcome variable for subsequent analyses in this study.

Exploratory factor analysis of app/website use data

An EFA was performed to explore whether there were any factors underlying the pattern of use of Skata app/web page types during users' visits 2 and beyond. Through an iterated principal factor approach to factor analysis 40 factors were identified in the item set. However, upon inspection of the parallel analysis plot (Figure 4.3) and difference in eigenvalues between factors, we determined a bend in the factor analysis curve and smaller differences in Eigenvalues beyond factor 5. So, we decided to use a 5-factor solution.

After performing an orthogonal rotation, several items loaded onto the five selected factors in patterns that could be described as motivations to use the Skata app/website (Table 4.6). Taken together these five factors explained 54.56% of the variability in the Skata app/webpage use data. The first factor had 9 app/web page types that loaded onto it with loadings ranging from .41 to .99, the factor explained 18% of the variability in use data, and the combination of pages loading on the factor could be described as depicting motivation to use Skata to make a contraceptive decision. The second factor had 5 app/web page types that loaded onto it with loadings ranging from .41 to .99, the factor explained 10% of the variability in use data, and the combination of pages loading on the factor could be described as depicting motivation to use Skata to scan for information, particularly about child education. The third factor had 4 app/web page types that loaded onto it with loadings ranging from .61 to .93, the factor explained 9% of the variability in use data, and the combination of pages loading on the factor could be described as depicting motivation to use Skata to scan for information, particularly about contraception. The fourth factor had 4 app/web page types that loaded onto it with loadings ranging from .43 to .97, the factor explained 9% of the variability in use data, and the combination of pages loading on the factor could be described as depicting motivation to use Skata to scan for information and plan for a family. The fifth and final factor retained had 5 app/web page types that loaded onto it with loadings ranging from .42 to .99, the factor explained 9% of the variability in use data, and the combination of pages loading on the factor could be described as depicting motivation to use Skata for time management. While each of the factors could be described as a psychographic motivation for using Skata, it is also important to note that the items that loaded onto factors often included nested pages within the app, thus also suggesting that factors reflected the architecture of Skata. Comparison of loadings for nested pages helps to reveal the depth to which users explored features within a sub-menu of Skata, such as the features contained in the contraception menu.

Regression analyses to predict engagement scores

Univariate analyses were conducted to assess the relationship of all demographic and Skata access characteristics on standardized EEI. All variables except estimated age were significantly correlated with standardized EEI (Table 4.7). In addition, factor scores were calculated for each of the five selected factors that emerged from the EFA. Each of these psychographic, motivational factors were then regressed on standardized EEI. All factors except for the time management factor were significantly associated with engagement. Thus the univariate analyses found that men were less engaged with Skata than females ($p<.001$), all individuals who provided sufficient registration data on marital status, age, parity and fertility goals to allow categorization into a life stage were more engaged with Skata than users who did not provide these data and were thus unassigned ($p<.001$), users who logged into Skata using their Facebook account were more engaged with Skata than those who logged on with an email address ($p<.01$), and while users who accessed Skata through the website alone were less engaged than users who accessed Skata through the app alone ($p<.001$), those who accessed Skata through both platforms were more engaged than app-only users ($0<.001$). In addition, the more users were motivated to use Skata for contraceptive decision making ($p<.05$), scanning about child education ($p<.001$), scanning about contraception ($p<.001$), or scanning and planning ($p<.001$) the more they engaged with Skata.

Curvilinearity of the relationship between engagement and one of the motivations for Skata use was tested. A regression of the Factor 1 representing motivation to use Skata for contraceptive decision-making and square of Factor 1 on standardized EEI was conducted to test for curvilinearity of the relationship between Factor 1 motivation and engagement. Results revealed no curvilinear relationship of Factor 1 and engagement, suggesting that this was simply a positive, linear relationship.

Interactions between several motivations for Skata use were tested. Regression results testing interactions between motivation to seek for contraceptive decisions making (Factor 1) and motivation to scan with a focus on contraception (Factor 3), as well as Factor 1 with the motivation to scan and plan (Factor 4) were not statistically significant. In addition, the interaction between Factors 3 and 4 was not statistically significant.

Based on these results a full, adjusted multivariate linear regression (MLR) model was developed. The full MLR model included all predictor variables that had a statistically significant univariate relationship with the standardized EEI (Table 4.7). From the adjusted model, higher standardized EEI scores were found among Skata users who were spacing and younger than 35 years of age ($p<.001$) as well as limiters ($p<.01$), as well as among Skata users who were motivated to use Skata for contraceptive decision making ($p<.001$) or a range of scanning motivations ($p<.001$ to $p<.01$). Skata users who accessed Skata through the website only had significantly lower standardized EEI scores compared to those who accessed only the app ($p<.001$). While the full MLR model explained 39% of the variance in standardized EEI scores, the AIC and BIC results suggest that there was still substantial variability unexplained by this model. The remaining variability was further underscored by Figure 4.4, where the overlay of a straight line for the fitted values and 95% confidence interval showed that the full model offered reasonable predictors of engagement with Skata, but that a substantial portion of the standardized EEI score data fell outside of this fitted line model.

Discussion

This study compared two ways to operationalize engagement with digital behavior change interventions, recommended the EEI as a robust measure of engagement, and identified demographic and motivational factors that predict engagement with the Skata mobile application and website. The EEI used in this study has strong face and content validity and moderately high internal reliability. In addition, compared against a typical length of use measure for engagement, the EEI has high criterion validity. This study also employed regression analyses to identify life stage, platform through which Skata was accessed and motivation for Skata use as statistically significant predictors of increased engagement with the intervention.

The relationship between life stage and engagement was not purely linear, but rather spacers under age 35 and limiters were significantly more engaged with Skata than registered users who had not completed the questions to assign a life stage. This suggests, controlling for demographic, access and motivational factors that users at these two stages of life found Skata content particularly enticing to explore. This is surprising given the common perception that digital interventions are most popular among younger audiences, such as newlyweds. However, Skata included a greater volume of content for spacers and limiters than it did for newlyweds – specifically, information about child development and childcare. Although EEI calculations accounted for the different content available per life stage, the availability of more content could explain why younger spacers and limiters engaged at higher levels than newlyweds.

The app platform used to access Skata was correlated with engagement. Specifically, use of the Skata website alone was associated with significantly lower engagement scores than accessing the program through the app alone. It is possible that once a user downloads the Skata app, it is simpler to continue to return to it. The app records one's login information – regardless of whether users choose to log in with an email address or Facebook account. So, after logging into the app for the first time Skata app users do not need to log in afterwards. In contrast, Skata website users must log into the website at each visit. If users forget the information they used to login, they may either cease to use Skata or they would need to set up a new account associated with a new unique identification number, and thus their usage data would underestimate the actual length of use for that individual. In addition, contraceptive information was available to users without requiring them to log into the website, so website users who returned to only use contraceptive content may not have logged in, thus underestimating actual length of use for Skata website users.

Several psychographic motivations to use Skata were significantly and positively associated with engagement. Each motivation represented a factor identified through an EFA of Skata usage data, and most factors included several nested pages. As a result, motivations may be a reflection of app/website architecture, while they also reflect the types of pages that users accessed in tandem with one another. Although including only the most granular pages from the app/website architecture may have produced cleaner results and identified fewer psychographic motivational factors, keeping nested pages and comparing the loadings helped to visualize how often users followed through to a subsequent level nested page, thus providing further insight into variability of click depth by topic area or sub-menu within the program. The four psychographic motivational factors that were significantly associated with engagement were similar in that interest in family planning and contraceptive topics drove Skata use. This is a logical result, and it is also a measure of success for the program because it suggests that, even when controlling for demographic and access characteristics, psychographic orientations that match the program's intended target audiences predicted increased engagement.

Limitations & Strengths

This study has several limitations. First, this study only captured data from registered Skata users, so people who chose not to sign into the app/website were not tracked as part of this study even if they returned to Skata several times. In addition, this study is a single application of the EEI to a single digital intervention and did not include the full suite of subscales in the EEI proposed earlier in this thesis. Additional applications of the scale are needed in a greater variety of contexts to build the scale's external validity. In particular, the EEI must be applied to DBCIs with a range of architectures to determine whether all of the subscales are applicable and remain consistent. Furthermore, the motivations for use identified in this study were based off of a pre-selected set of pages of the Skata app that included nested pages. The effect of including the nested pages may have lent itself to development of factors that were termed motivations for use. By including only the most granular pages – the lowest level pages in the app/website architecture – we may have achieved a different factor solution with fewer, and less distinct motivational factors. The length of the study may have also affected conclusions about motivations for using Skata. Specifically, this study examined a 5-month period during which Skata users registered and were tracked on a rolling basis. If the study included a longer period of data collection it is possible that it could have captured re-engagement with the program, possibly driven by a different motivation. While this study treated visits 2 and above as similar, with a longer length of study there may have been more discrete time breaks to compare to understand how motivations for use shift with time.

In this study the final regression model accounted for less than half of the variability of the standardized EEI scores. More research is required to understand what other factors may predict engagement, so that those can be incorporated into the regression model. While this study included only data produced through app use and captured as data exhaust, it is possible that factors external to app use, such as interpersonal communication about the health topic or behavior, may contribute to explaining the variability in engagement scores. Further research should consider how to incorporate interpersonal factors into regression models to test their relationship with DBCI engagement. In addition, the pattern of residuals from the MLR may exhibit non-constant variance. Further studies may apply data transformations to explore non-constant variance to explore further insights into the heterogeneity of user behavior. The regression results of this study are also not generalizable beyond digital interventions for family planning behavior change. Although the methods may be utilized to determine factors motivating engagement with other DBCIs, the interpretation of factors resulting from an EFA of a different app/website would likely be specific to the topic(s) being addressed. Demographic factors such as life stage may also be less applicable outside of family planning. The technology infrastructure context may also play a role in determining whether app/website access factors predict engagement, with platform being less associated with engagement in contexts where multi-platform Internet access is commonplace.

Finally, this study did not include any assessment of behavior change, so relationships between engagement and behavior change could not be tested. While the EEI weights all subscales equally, testing them individually against a behavioral outcome may reveal some to be more predictive than others of change and thus prompt reconsideration of the relative weight of the subscales within the EEI. In addition, comparing EEI scores with behavior change indicators would be an avenue for future research to conduct convergent and discriminant validity tests.

Despite its limitations, the study has several strengths. The EEI, applied in this study as an outcome variable, is noteworthy for its reliance on Skata data exhaust. These data, a byproduct of app/website use, were unobtrusively collected and thus offer a way to conduct valuable research while minimizing participant burden, more economically allowing for long lengths of study and eliminating the effects explicit observation may have on intervention use. Rather than relying on recall of use after-the fact, data exhaust captures use in real time to also eliminate the possibility of recall bias. By using data exhaust in this study, we were also able to examine data from a large sample of Skata users. This study also went beyond scale development, utilization and testing to offer an analysis of predictors of engagement. The study used a creative approach to identify motivations for Skata use and to incorporate those motivations into a model for engagement.

Conclusion

It is important to study engagement with DBCIs and rigorously measure this phenomenon to gain valuable process monitoring and outcome evaluation insights. There is growing use of digital strategies in social and behavior change programs. Measurement methods must be developed and tailored to suit this unique communication channel. The EEI provides a valid, burden-free and objective tool for assessing engagement with DBCIs. The use of EEI as an outcome measure is beneficial in process evaluations to identify whether the DBCI is targeting and retaining people with motivations that match the program's objectives, and to understand what else may be associated with high engagement with the intervention. This study exemplifies the ways in which the EEI can help programs better understand who comprise their most engaged audience and what features of the intervention are driving engagement.

Table 4.1: Description of pages tracked in Skata app that load onto factors in EFA, with indication of nested pages

Short description of page and action tracked	Full description of page and action tracked
Main menu	User opens the main menu
1. Contraception menu	User views the main contraception section
a. Contraceptive information	User opens the menu listing all modern contraceptive methods
i. Find the right contraceptive for me	User answers a series of questions to determine the most effective contraceptive method for their fertility goals
b. Add contraceptive reminder	User adds the type of contraceptive s(he) uses and the date it was last used to calculate a reminder for when to replace/use the next contraceptive
c. Menstrual calendar	User views the menstrual calendar reminder feature
i. Add menstrual calendar data	User adds the dates of her last period to calculate when to expect her next period
2. Counseling menu	User views the main counseling section
a. Counseling categories	User browses the counseling frequently asked questions (FAQs) categories (e.g., Pregnancy)
i. Counseling list of questions within an FAQ category	User views the list of questions within a counseling FAQ category (e.g., What are the risks of pregnancy over age 35?)
1. Specific counseling information	User views one of the counseling FAQ answers in detail
a. Rating counseling information	User rates satisfaction with specific counseling FAQ answer provided
3. Family planning menu	User opens the family planning section
a. School calendar	User views the school calendar feature
b. Listing of children	User opens a feature that shows sub-menus for each child the user has added in the app
c. Education planning feature	User views the educational planning feature, where schooling levels are listed (e.g, Primary, Secondary) up to the planned education attainment level, per each child added in the app
i. Add child's planned education attainment level	User selects the level to which they plan to educate their child (e.g., though high school, through college, etc), per each child added in the app
ii. Check child's educational attainment	User marks levels of education their child has attained against planned education goals, within the educational planning feature, per each child added in the app

Short description of page and action tracked	Full description of page and action tracked
4. Article list	User views the list of articles
a. Specific article	User views a specific article
5. My Plan feature	User answers a series of questions to get individually tailored feedback about spacing and limiting children. Feedback includes a detailed timeline of the user/couple's life until approximately age 70
6. To do list	User types in a new to do list
a. Add task	User adds a new task to a to do list
i. Check task	User checks off a completed task on a to do list
ii. Delete task	User deletes a task from a to do list
7. Developmental milestone checklist	User marks developmental milestones child has achieved through age 5, per each child added in the app
8. User profile	User views his/her profile page

Table 4.2: Summary statistics for a sample of tracked app/web page

	Overall (n=15,909)		First Visit (n=15,909)		Visits 2-3 (n=7,406)		Visits 4+ (n=2,514)	
Page	**Mean number times accessing page**	**Std dev**	**Mean number times accessing page**	**Std dev**	**Mean number times accessing page**	**Std dev**	**Mean number times accessing page**	**Std dev**
Article menu								
List of articles	2.320	3.255	1.169	1.351	1.248	1.678	3.835	4.783
Specific article	1.393	2.832	0.652	1.400	0.771	1.999	2.737	4.475
Counseling								
Find the nearest midwife	2.760	6.930	1.544	3.966	1.163	4.217	4.563	10.997
Counseling menu with FAQ topics	0.254	1.159	0.219	1.016	0.050	0.433	0.076	0.687
List of questions within an FAQ topic	1.178	2.504	0.634	1.600	0.552	1.572	1.996	3.322
Specific answer to FAQ	2.004	5.259	1.113	3.578	0.955	3.610	3.332	7.166
Contraception								
Quiz about contraception	2.444	7.072	1.417	5.015	1.067	4.388	3.998	9.600
Contraception menu	0.229	1.098	0.195	0.824	0.035	0.303	0.089	1.022
List of contraceptive methods	0.189	0.992	0.169	0.898	0.038	0.465	0.028	0.544
Find the right method for me feature	0.066	0.368	0.059	0.341	0.014	0.269	0.010	0.153
Specific contraceptive method information	1.882	4.794	1.117	4.013	0.768	2.025	2.278	4.349
My Plan feature |	1.755	3.079	1.006	1.753	0.719	1.491	2.655	4.136
Child developmental milestones	1.680	4.390	0.930	2.665	0.703	2.279	2.876	5.969
To do list	0.713	2.807	0.447	1.757	0.290	1.817	0.959	3.293
Feature breadth	6.689	3.549	7.682	4.407	4.621	2.783	3.925	2.190

Table 4.3: Demographics and app/website access characteristics of Skata registered users overall and by two outcome variables

Characteristics	Total sample ever visited Skata (n=15,909)	Length of use of Skata app: Less than one month use (n=13,658)	Length of use of Skata app: One month or more use (n=2,251)	p-val	Standardized Extended Engagement Index (EEI): Low engagement (n=9,159)	Standardized Extended Engagement Index (EEI): High engagement (n=6,750)	p-val
Estimated age (%)							
-12-17 years	0.41	0.40	0.49	0.537	0.28	0.59	**<0.05**
-18-24 years	28.68	27.56	35.45	**<.001**	22.87	36.55	**<.001**
-25-34 years	31.38	29.86	40.60	**<.001**	26.33	38.22	**<.001**
-35-44 years	1.89	1.74	2.80	**<.001**	1.63	2.24	**<.01**
-45-55 years	0.60	0.45	1.51	**<.001**	0.31	1.01	**<.001**
-Not available	37.04	39.99	19.15	**<.001**	48.58	21.39	**<.001**
Mean estimated age in years (sd)*	25.42 (4.68)	25.32 (4.54)	25.88 (5.24)	**<.001**	25.44 (4.44)	25.40 (4.89)	.628
Gender (%)							
-Female	69.00	67.37	78.85	**<.001**	62.85	77.35	**<.001**
-Male	16.79	17.25	13.99	**<.001**	18.46	14.52	**<.001**
-Not available	14.21	15.38	7.15	**<.001**	18.69	8.13	**<.001**
Life stage (%)							
-Unmarried	5.03	4.93	5.64	.153	4.56	5.66	**<.01**
-Newlywed, <35 years	15.28	14.95	17.28	**<.01**	14.20	16.74	**<.001**
-Newlywed, 35 years+	2.76	2.77	2.71	0.872	2.72	2.81	0.732
-Spacing, <35 years	31.43	29.50	43.14	**<.001**	23.36	42.37	**<.001**
-Spacing, 35 years+	4.53	4.32	5.78	**<.01**	3.69	5.66	**<.001**
-Limiting	7.06	6.44	10.84	**<.001**	5.10	9.72	**<.001**
-Not assigned	33.92	37.10	14.62	**<.001**	46.36	17.04	**<.001**
Mean days of use (sd)	12.65 (27.87)	2.75 (6.07)	72.77 (32.50)	**<.001**	1.96 (10.85)	27.16 (36.13)	**<.001**
Mean number of	2.28 (2.50)	1.71 (1.27)	5.77 (4.51)	**<.001**	1.10 (0.39)	3.88 (3.18)	**<.001**

Characteristics	Total sample ever visited Skata (n=15,909)	Length of use of Skata app: Less than one month use (n=13,658)	One month or more use (n=2,251)	p-val	Standardized Extended Engagement Index (EEI): Low engagement (n=9,159)	High engagement (n=6,750)	p-val
visits (sd)							
Login method (%)							
-Facebook	62.66	62.40	64.19	0.104	61.38	64.39	**<.001**
-Email address	37.34	37.60	35.81	0.104	38.62	35.61	**<.001**
Platform used to access (%)							
-App only	80.45	77.78	96.62	**<.001**	69.79	94.90	**<.001**
-Website only	19.28	22.03	2.62	**<.001**	30.16	4.53	**<.001**
-Both	0.27	0.19	0.76	**<.001**	0.05	0.56	**<.001**
Mean standardized EEI score (sd)	-.004 (.773)	-.141 (.711)	0.826 (.591)	**<.001**	-.580 (.271)	0.778 (.495)	**<.001**

*Mean estimated age only includes individuals for whom age data was available. The total sample ever visited Skata n=10,016, less than one month use n=8,196, one month or more use n=1,820, low engagement n=4,710 and high engagement n=5,306.

Table 4.4: Correlation between standardized EEI subscales, Chonbach's Alpha = .8630

EEI subscales	Click depth	Duration	Loyalty	Interaction	Recency	Feature breadth
Click depth	1					
Duration	.5602	1				
Loyalty	.7803	.6057	1			
Interaction	.4316	.3038	.4434	1		
Recency	.6228	.4238	.6096	.2991	1	
Feature breadth	.5940	.6479	.6107	.3438	.4055	1

Note: All correlations are significant at p<.001

Table 4.5: Comparing mean EEI subscale scores by two engagement outcome variables

		Length of use of Skata app			**Extended Engagement Index**		
EEI subscales Mean (sd)	**Total sample** (n= 15,909)	**Less than one month use** (n=13,703)	**One month or more use** (n=2,253)	**p-value**	**Low engagement** (n=9,193)	**High engagement** (n=6,763)	**p-value**
Click depth	0.534 (0.267)	0.489 (0.252)	0.806 (0.180)	**<.001**	0.339 (0.103)	0.797 (0.182)	**<.001**
Duration	0.384 (0.207)	0.356 (0.192)	0.554 (0.214)	**<.001**	0.272 (0.130)	0.531 (0.198)	**<.001**
Loyalty	0.135 (0.177)	0.092 (0.140)	0.397 (0.145)	**<.001**	0.014 (0.050)	0.300 (0.152)	**<.001**
Interaction	0.091 (0.076)	0.083 (0.071)	0.141 (0.086)	**<.001**	0.061 (0.056)	0.132 (0.081)	**<.001**
Recency	0.005 (0.009)	0.005 (0.009)	0.006 (0.008)	**<.001**	0.000 (0.002)	0.012 (0.009)	**<.001**
Feature breadth	0.097 (0.053)	0.089 (0.049)	0.143 (0.053)	**<.001**	0.069 (0.035)	0.134 (0.048)	**<.001**

Table 4.6: Factor loadings from the structure matrix with orthogonal rotation with app pages listed to indicate page nesting

Short descriptions of Skata app pages	**Factor 1** (Proportion= 18.44%) **"Contraceptive decision making"**	**Factor 2** (Proportion= 9.76 %) **"Scanning with focus on child education"**	**Factor 3** (Proportion= 9.12%) **"Scanning with focus on contraception"**	**Factor 4** (Proportion= 8.74%) **"Scanning and planning"**	**Factor 5** (Proportion= 8.50%) **"Time management"**
Main menu	.8549				
1. Contraception menu	.7603				
a. Contraceptive information	.4076				
i. Find the right contraceptive for me	.9897				
b. Add contraceptive reminder	.8786				
c. Menstrual calendar	.7189				
i. Add menstrual calendar data	.9646				
2. Counseling menu	.8290				
a. Counseling categories			.7347		
i. Counseling list of questions within an FAQ category			.9335		
1. Specific counseling information			.8453		
2. Rating counseling information			.6127		
3. Family planning menu	.9759				
a. School calendar		.5581			
b. Listing of children		.4078			
c. Education planning feature		.9949			
i. Add child's planned education attainment level		.8797			

Short descriptions of Skata app pages	**Factor 1** (Proportion= 18.44%) **"Contraceptive decision making"**	**Factor 2** (Proportion= 9.76 %) **"Scanning with focus on child education"**	**Factor 3** (Proportion= 9.12%) **"Scanning with focus on contraception"**	**Factor 4** (Proportion= 8.74%) **"Scanning and planning"**	**Factor 5** (Proportion= 8.50%) **"Time management"**
ii. Check child's educational attainment		.8963			
4. Article list				.9681	
a. Specific article				.7467	
b. My Plan feature				.4280	
5. User profile				.7790	
6. To do list					.6140
a. Add task					.9687
i. Check task					.4705
ii. Delete task					.9941
7. Developmental milestone checklist					.4186

Table 4.7: Regression on stdEEI: Betas and p-values from SLRs and MLR with demographics and motivation factors

	Univariate model (Beta)	**P-value**	**Adjusted model** (Beta)	**P-value**
Estimated age	-.002	.248	--	
Gender – female (ref)				
-Male	-.223	**<.001**	.126	.357
Life stage – unassigned (ref)				
-Unmarried	.576	**<.001**	.473	.174
-Newlywed, <35 years	.519	**<.001**	.245	.199
-Newlywed, 35 years+	.492	**<.001**	.305	.526
-Spacing, <35 years	.761	**<.001**	.449	**<.001**
-Spacing, 35 years+	.666	**<.001**	-.142	.547
-Limiting	.772	**<.001**	.378	**<.01**
Login method – Email address (ref)				
-Facebook	.037	**<.01**	.106	.292
Platform used to access – App only (ref)				
-Website only	-.802	**<.001**	-.811	**<.001**
-Both	.633	**<.001**	.016	.963
Factor 1: **Motivation to seek, for contraceptive decision-making**	.121	**<.05**	.181	**<.001**
Factor 2: **Motivation to scan with focus on child education**	.180	**<.001**	.125	**<.01**
Factor 3: **Motivation to scan with focus on contraception**	.252	**<.001**	.227	**<.001**
Factor 4: **Motivation to scan and plan**	.290	**<.001**	.242	**<.001**
Factor 5: **Motivation to use time management tools**	.084	.087	--	--
R^2	--		.3940	
AIC			515.16	
BIC			568.16	

Figure 4.1: Days of use histogram (n=15,909)

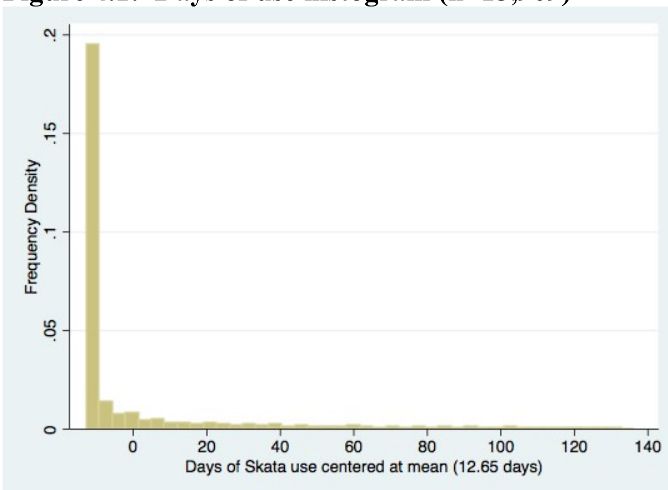


Figure 4.2: Z-score standardized EEI histogram (n=15,909)

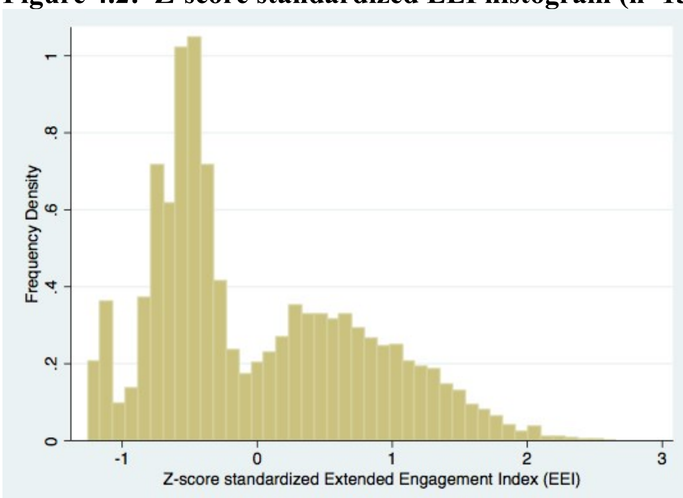


Figure 4.3: Parallel analysis of factor analysis with iterated principal factors for Skata feature use in visits 2 and beyond

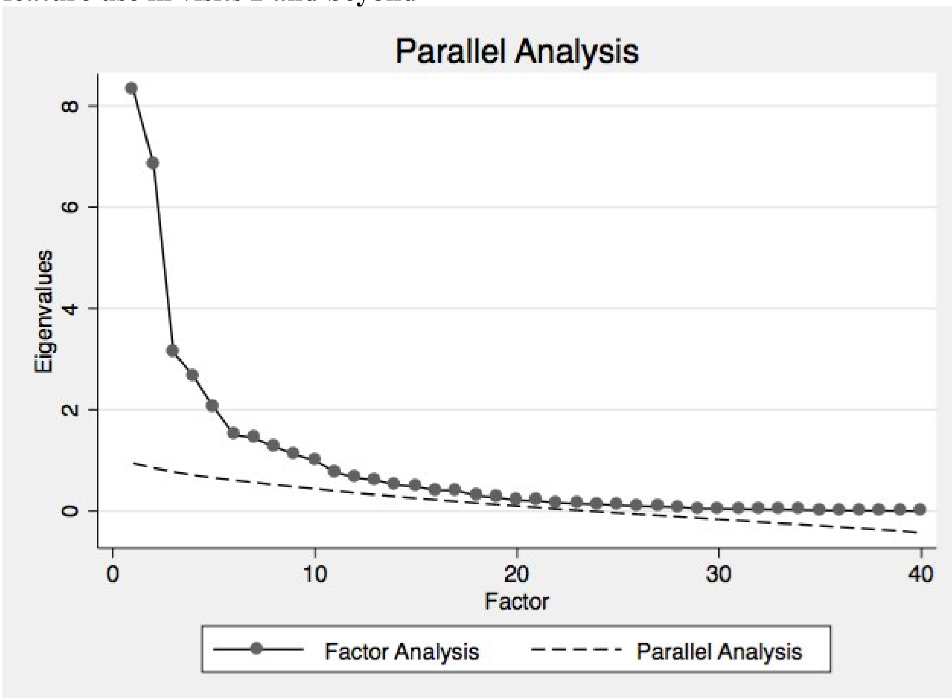
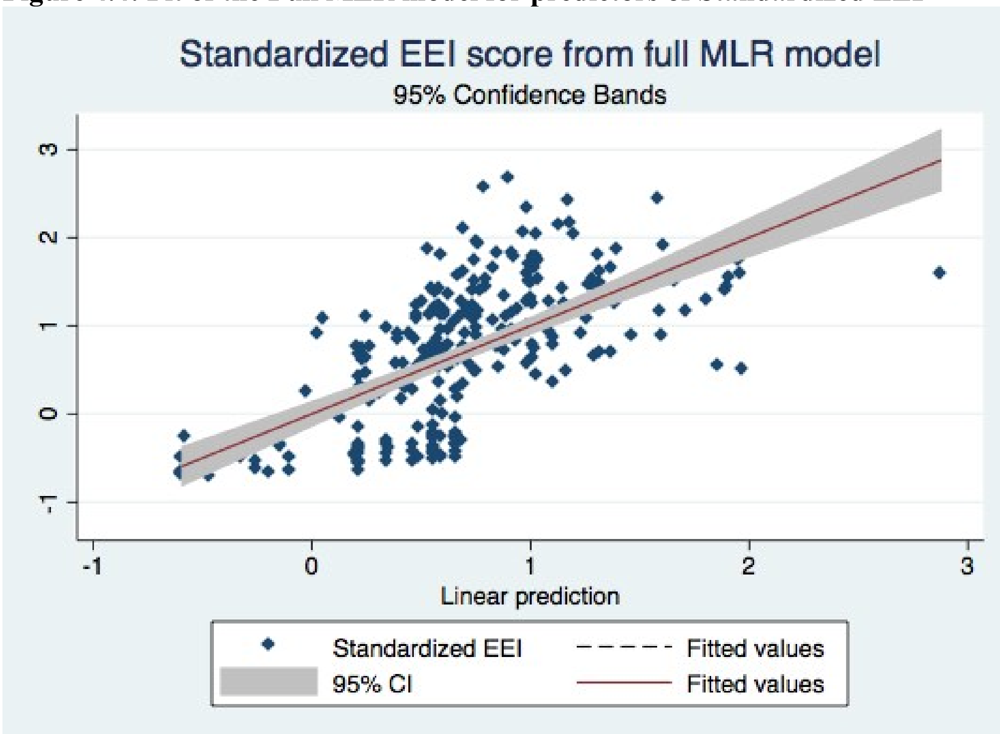


Figure 4.4: Fit of the Full MLR model for predictors of Standardized EEI



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Chapter 5: The role of motivation in shaping experiences of engagement:

Exploration of use of the Skata mobile application for family planning in Indonesia

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Chapter 5 – The role of motivation in shaping experiences of engagement: Exploration of use of the Skata mobile application for family planning in Indonesia

Abstract

This study explores the relationships between motivation for use and engagement in digital behavior change interventions (DBCIs) within the context of Skata, a mobile application for family planning decision-making and contraceptive method change in Indonesia. Depending on motivation for DBCI use, goals for 'adequate engagement' to achieve behavior change may vary. The findings of the qualitative study indicate that most users were initially motivated to scan the DBCI to increase their general understanding of fertility planning and contraceptive options. For these users, a threshold of 'adequate engagement' did not apply, as they had no intention of behavior change. In comparison, 'adequate engagement' was relevant to assess among users motivated to seek decision-support about fertility planning and contraceptive decisions. However, engagement with the DBCI represented a subset of users' engagement with the topic. Interpersonal communication played an important role in influencing behavior change. The role of interpersonal communication, or sharing, also influenced DBCI engagement and may have affected motivations for DBCI use.

Background

Despite Indonesia's long history of national support for family planning (FP), the modern contraceptive prevalence rate (mCPR) has been stalled at around 60 percent for over a decade, since 2003, and was recorded at 57.2% in 2017 (DHS Indonesia 2017). Furthermore, the FP method-mix has shifted towards heavy use of short-term methods such as injectables and oral contraceptives over the last 20 years, with 32% and 14% of married FP-using women ages 15-49 using injectables and oral contraceptives in 2012 compared to 12% and 15%, respectively in 1991 (DHS Indonesia 2012). The Skata mobile application (app) was launched in Indonesia in April

2016 as a demand-generation strategy to encourage family planning use, and particularly use of long-acting reversible contraceptives (LARCs) that are more effective methods for long-term spacing and limiting of pregnancies. Skata was positioned as a lifestyle intervention to help women and their partners plan for major life events related to having a family, such as planning for marriage and children, and in concert with those plans selecting the most appropriate contraceptive method to match the couple's fertility goals.

The Skata mobile application was developed by Mobile Force, a company based in Jakarta, Indonesia. The Johns Hopkins Center for Communication Programs (CCP) provided oversight during the app development process and supported testing of the app through a grant from the Bill and Melinda Gates Foundation. The app was available through the Google Play and iOS App stores, as well as through the website www.skata.info. The app was supported by social media assets such as Facebook, Instagram and Twitter pages, but these assets were not directly accessible through the app.

Engagement with Skata was hypothesized to be a precursor to changing users' awareness of the full range of contraceptive methods available, knowledge about and attitudes towards those methods, as well as normative perceptions of whether Indonesian women use LARCs. Operating through these psychographic mechanisms, the program believed Skata could affect behavioral changes such as contraceptive adoption, and adoption of LARCs in particular.

Engagement with digital behavior change interventions (DBCIs) has been discussed as a multi-stage phenomenon. O'Brien and Toms broke engagement into four stages: 1) the point of engagement, 2) a period of sustained engagement, 3) disengagement, and 4) re-engagement (2008).

During the period of engagement, digital behavior change intervention (DBCI) programs focus on achieving 'adequate engagement' to move users towards taking action for behavior change. However, 'adequate engagement' can be a difficult threshold to determine with DBCIs.

Ritterband et al. note that some users may be able to satisfy their needs by using a limited subset of a DBCI while others may use the full scope of the DBCI (2009).

To make sense of DBCI usage data, including instances of disengagement and patterns of re-engagement, it is important to understand the motivations driving engagement. While a few studies have shown a relationship between perceived usefulness of a digital intervention and engagement measured as intervention use (Nitsch et al 2016, Blumenthal-Barby 2016), little is known about how perceptions of utility for a DBCI may differ across users of the intervention. If users perceive the utility of the intervention to be different – that the intervention is useful for different purposes – it is conceivable that differing motivations for engagement may reflect in differing patterns of intervention use.

Health information seeking literature focuses on clarifying one distinction in motivations for health media consumption: outlining the difference between seeking and scanning for information. Health information seeking focuses on active efforts to gather information, exhibiting non-normal patterns of media exposure or interpersonal communication (Atkin 1973). It is distinguished from scanning, which is described as less active and less goal-oriented than seeking and characterized by routine or habitual use of media and interpersonal communication (Morris, Rooney, Wray, & Kreuter, 2009; Niederdeppe et al., 2007).

Gratifications are a complementary way to represent the latent goals that motivate an individual's use of media. In Uses and Gratifications theory (U&G) media consumers play an active role in selecting the media they would like to use and consuming the messages within it. The goals of media consumption may include a need to survey the landscape to gather factual knowledge, gathering social knowledge such as reinforcement of one's attitudes, deeper personal insight, or correlational information, or a need for diversion (McQuail, Blumler & Brown 1972, Katz, Blumler & Gurevitch 1973). Though all media consumption is considered active, some gratifications could be considered scanning functions, such as gathering types of knowledge and finding diversions. Consumption of other media features may be more instrumental in seeking support for decision-making, including gaining personal insight and gathering correlational information. In the realm of digital media, information-gathering and social relationship development gratifications can be nuanced, may overlap, and may be shaped by the features afforded by the digital media (Sundar & Limperos 2013). No research has been done to understand the constellation of gratifications that motivate use of a DBCI focused on family planning and contraception in Indonesia.

The Indonesian context is unique for exploration of relationship building gratifications motivating DBCI use, because it represents a collectivist cultural context. The Hofstede Centre applies a six-dimensional Hofstede Insights model to comparing cultures, including a dimension measuring a country's individualism or "the degree of interdependence the society maintains among its members" (Hofstede Insights, accessed November 2017). Indonesia scores 14 out of 100 for being an individualistic culture, meaning there is a strong societal norm towards conformation, which bears out as others having strong influence on the individual's choices and actions, and a sense of duty to make influential others' lives easier. In this context, an individual intervention such as a mobile application may be used in unique ways. Past studies of engagement have often focused on Western contexts where the cultural context is more individualistic (El-Hilly et al. 2016, Estrada et al 2017, Taki et al. 2017, Hofstede Insights, accessed November 2017). To date there have not been studies that incorporate cultural context into an exploration of motivation for use and engagement with DBCIs.

Methods

In January through April 2016 a two-person research team conducted a two-part series of interviews with adult, married women of reproductive age (age range 18-42) in three locations in Indonesia. Participants provided verbal consent to participate in the research (see Appendix 7). The three research locations were East Jakarta, Brebes and Asahan. East Jakarta represented a low to middle-income urban area with high technology infrastructure, while Brebes and Asahan were more rural with lower income participants and less technology infrastructure.

The two rounds of interviews varied slightly in their focus. The first interview focused on Skata app usability, allowing new app users the opportunity to download and navigate the app for the first time during the interview session (see Appendix 8 for interview guide). The second interview took place approximately one month later and focused on app use over time. This interview was purely conversational, asking participants to recount what aspects of Skata they had used, when, and how they had talked about Skata with others in their family and community (see Appendix 9 for interview guide).

Interview coding used a framework analysis approach informed by the Uses and Gratifications theory. This theory and its more recent extensions outline the many facets of a 'need to be connected' that drive communication, and use of particular communication mediums (Katz, Blumler & Gurevitch 1973).

Participants

Eligible study participants were adult married females, who represent the main target audience for the Skata communication intervention. In addition, women were selected to represent one of three life stage categories: newlyweds with no living children, women who had at least one child and were potentially interested in spacing their next pregnancy, and women who had at least one child and were interested in no longer bearing children. In addition, women either indicated that they did or did not use a female modern method of family planning (FP). To ensure that participants would be able to interact with a mobile application, eligible women were required to indicate basic familiarity with mobile apps by having at least two apps downloaded to a mobile phone that they used regularly, or by reporting that they used the Internet on a mobile device at least once per week.

A total of 34 participants were recruited, and three were lost at one-month follow-up, resulting in 65 interviews total (Table 1). Though participants were sampled to generally represent equal numbers of participants across three life stages (newlywed, spacing and limiting), there was some heterogeneity within these categories. For example, among the ten newlyweds interviewed, two were pregnant, four were trying to conceive and another four were trying to delay having their first child. Among the 12 women who said they were interested in spacing, two were actually trying to have a next child and thus simply represented women with parity 1 or higher. Among the 12 women who said they were interested in limiting, two were not certain that they wanted to limit childbearing at the time of their first interview. In addition, FP users referred to *current use* of contraception. Users were generally defined as women currently using a modern method of contraception, while non-FP users were either currently not using any contraception or were currently using natural methods. Condom users, however, were split depending on whether the women said their spouse used a condom every time they had intercourse (FP user) or used a condom sometimes (non-FP users).

Interview participants were asked a series of questions included in the Media and Technology Usage and Attitudes Scale (MTUAS, Rosen et al. 2013) to gauge their technology aptitude, specifically with respect to mobile phone literacy. Nearly all participants could perform basic functions on their phone such as adding a new contact (32 out of 34 participants), managing battery life (33/34 participants), accessing the calendar (33/34), adjusting volume 34/34), navigating the Internet (33/34), opening an app (31/34), and playing audio or video (34/34). Ability to download apps, however, varied with 24/34 saying they could, nine saying they could not and one unsure. Most newlywed women and those who were trying to space their children were confident in their ability to download an app (eight of 10 newlyweds and 11 of 13 spacers said they could download an app). Women who are trying to limit their children, however, demonstrated mixed ability with just five of 11 limiters saying they could perform this function without assistance. While most participants knew how to access a Wi-Fi network on their phone

(26/34), this was not a universal capability. Ability to use GPS also varied, with about half of women in East Jakarta (6 in 10) saying they could use this function, compared to most women in Brebes and Asahan saying they could not (8 in 11, 9 in 12, respectively).

Recruitment methods

Independent consultants in each location recruited the study participants. In East Jakarta the recruiter was a freelance researcher who went door-to-door in several subdivisions of the city, screening for eligible women and recruiting them to participate in the study. In Brebes and Asahan the recruiters were also employed by the local BKKBN (Indonesian National Office of Family Planning). These recruiters used lists from their local BKKBN offices that indicate the contraceptive use status of each resident in a cachement area to identify family planning users and non-users, and participants included local BKKBN office staff.

Participants were asked to participate in two rounds of structured interviews. The interviews took place at participants' homes, at a time of their convenience. The first interview lasted approximately 1.5 hours and included downloading the Skata app, navigating it and discussing initial impressions. At the end of the first interview participants were instructed to use the Skata app at their leisure in the time leading up to their second interview. The second interview took place approximately one month later, and participants were asked to recount their experiences using (or not using) the Skata app, and how they discussed the app with household members, community members, social network connections and healthcare providers.

Analysis methods

Interviews were audio recorded, transcribed in Bahasa Indonesia and then translated into English. A coding framework was developed based on typical gratifications from Uses and Gratifications literature (Katz, Blumler & Gurevitch 1973), and collapsed into two categories: gratifications for scanning vs. gratifications for seeking. This framework analysis approach was used in the analysis of first round interviews to identify participants' initial motivations for using

Skata. Participants were classified as having no initial motivation, a motivation for scanning, or a motivation for seeking further parsed into motivations to seek for the purpose of planning fertility goals vs. making a contraceptive decision. Using this classification scheme, discussions of app feature use in first and second round interviews were compared to reveal differences in engagement patterns by initial motivation for DBCI use. A second round of coding was applied to identify instances of sharing or interpersonal communication, and these instances were also compared by initial motivation for DBCI use.

Skata overview

In its initial configuration, Skata offered several menu categories, as shown in Figure 5.1. The main menu included links to features and sub-menus including articles, contraceptive information, counseling, family planning and child-rearing information, checklists and a planning feature. Descriptions of each sub-menu follow:

- Artikel: The articles section of Skata included articles written on a range of topics related to family relationships, contraception, and raising children. Approximately two new articles were added every two weeks during the testing period.
- Kontrasepsiku: The contraceptive information section of Skata included a sub-menu with information about modern methods of contraception, a feature that helped users 'Find the right contraceptive for me,' and a quiz feature that tested knowledge about contraceptives. It also included a menstrual calendar that predicted a user's next ovulation period and menstrual period based on last menstruation. Finally, it included a contraceptive reminder feature to determine when a user would need to take or receive their next contraceptive device.
- Konseling: The counseling section included a sub-menu for 'Ask a midwife,' offering information about reproductive health and contraceptives in a frequently asked questions

format, and a ‘Find the nearest midwife’ feature that used GPS to list midwives and hospitals in the vicinity of the app user.

- Perencanaan Keluarga: The family planning section included calendars to help with planning for family events and childcare such as immunization schedules, a school calendar and a checklist for planning children’s educational attainment goals.
- Perkenbangan Anak: The child developmental milestone section included age-based developmental milestones for healthy children ages 0-5 years.
- Daftar Target: The checklist section included two checklists – a daily checklist and a general checklist, both that could be modified by the user. The checklists allowed users to track to-do items that they needed to accomplish in the short-term (e.g., pick child up from school) and the long-term (e.g., doctor’s appointment).
- Rencanaku: The My Plan section included a series of questions asking users the year of their wedding, how many children they plan to have and when they plan to have each child. The questions were used to create a life simulation document that detailed a couple’s life milestones from marriage until age 70 of the user’s life. The My Plan document included calculations about what age the user would be when their oldest child finished high school (to prompt thoughts about age for limiting childbirths) and whether their child spacing would result in having to pay double school fees at some point (when two children entered a new school simultaneously). It also contained risk-related warnings for plans that included pregnancy after age 35.
- Pengaturan: The settings section allowed users to adjust their profile in the app, including their number of children. Initial profile settings were created when users registered with the app at first login. The settings were used to tailor app content such as articles and child-related features to only appear for users who indicated that they had children.

The development of the app was based on assumptions about the purposes for app use by life stage. It was thought that newlyweds in particular would want to plan for their future, and women either delaying, spacing or limiting would be interested in Skata for assistance in making a contraceptive decision. 'Lifestyle features' were incorporated to appeal equally across life stages. These features included daily life planning features such as checklists, self-monitoring features for tracking menstrual cycles, and cues to action to ensure timely use or insertion of contraceptive methods. In addition, articles covered a broad range of topics including family relationships and general health to appeal to all users, with more specific information about child development and childcare included to appeal to users who had children (spacers and limiters). These assumptions shaped decisions about content to include and how content was tailored to registered Skata users who logged into the app.

Results

Life stage was used to stratify sampling in this study, with the underlying assumption being that participants in a given life stage would use Skata for similar reasons. However, through the interviews in this study, it became apparent that life stage was a less meaningful classifier of app engagement experiences than participants' reason for their initial interest in Skata. Initial, primary purposes for wanting to use Skata did not completely align with life stage (Table 5.2). Rather, the majority of participants first expressed an interest in Skata for use to gather information on a variety of topics including general health, childcare, family relationships, pregnancy and contraception. These participants saw Skata as a tool for scanning – they were not engaged in a particular decision-making process related to Skata content, but wanted to keep abreast of family, reproductive and contraception-related information. Scanning users included a mix of life stages - about half of the newlyweds, and most women interested in spacing or limiting.

About one-third of participants initially or over the course of one month of Skata use began seeking information in Skata as they engaged in planning or decision-making related to Skata content. Women planning for their family's future were largely newlyweds, making decisions about fertility goals and planning for the development milestones of children in their future. A few women were engaged in or started to consider a contraceptive decision during the study period. These participants – all of whom had at least one child – discussed how Skata played a role in their decision-making process as they contemplated a method, prepared to make a change or adopted a new method.

While most women interviewed expressed interest in Skata for scanning or seeking, a few said that the app did not serve any particular purpose in their life at the moment. These women felt no motivation to use Skata during the initial interview.

Women who expressed more than one initial motivation for using Skata were categorized according to the following hierarchy: 1) seeking for contraceptive decision making, 2) seeking for planning for the future, 3) scanning.

The length of engagement, engagement patterns and end goal of engagement varied depending on participants' motivation for using Skata. Scanners had the potential to engage for a long period of time, with no concrete end goal to achieve, and a broad approach to exploring the app for new content. In comparison, seekers were motivated to make a fertility plan or a contraceptive decision and behavior change. Their engagement with content was directed to satisfying those needs, and this intense period of engagement had a defined end when planning or decision-making was completed.

The following sections of the results trace the ways in which participants with differing initial motivations engaged with Skata over the one-month study period.

No initial motivation

At the initial interview, three participants voiced no initial motivation to use Skata. These participants did not intend to prioritize making time in their lives to use the app. Generally the participants did not think Skata content was relevant to their lives at that moment, but could see the potential utility of it for the future.

> "I'm currently using IUD. My plan is to have it removed 6 months from now. Yes [I plan to have another child], but later...Based on theory and my experience in the field [as a midwife], most of the [contraceptive] information is the same, so I trust it… In fact, I think this app doesn't contain just contraception and family planning, but it has information about child development, preparation and planning for education as well. [Skata] will [influence my thoughts] for planning, particularly for the children. We can also look at what's in store for the future." – Brebes, Spacer, No motivation

> "[It's suitable] for me to read through. Basically, as long as a person is married he or she can use this program. For example, when I have time, when there is nothing to do, in the evening after ironing." – East Jakarta, FP user, Limiter, No motivation

The three participants with no initial motivation to use Skata followed different paths in engaging with Skata after one month. One was lost to follow-up, as she had moved to a new city for a work opportunity. Another had not used Skata in the month, unable to overcome technical issues with her phone and install the application. Her story underscores the importance of mobile phone literacy and availability of technical support as contributing factors that could shift users with little motivation to use Skata into either a scanning or seeking stage.

> "I couldn't [install the app]. I asked a friend, and we still couldn't do it. I tried several times but I couldn't do it at all. Well, then I stopped trying. I actually wanted to go to [a local shopping and electronics center], but it rained every day, so I couldn't go. I was concerned the memory is full, so some stuff may need to be deleted so that I can install applications again." – East Jakarta, FP user, Limiter, No motivation

Initial motivation to scan

Initially, 20 participants introduced to Skata were interested in continuing to use the app for scanning purposes – primarily to stay abreast of topics related to family, children, general and reproductive health and contraception. Participants felt this was important information to know about, and that tips for improving family relationships, promoting good health and caring for children were useful to their daily lives. The article feature was often used to fulfill a need for scanning and surveillance. As a mobile app, Skata offered an advantage over traditional means of information gathering by curating articles relevant to family life and making then conveniently available. The article feature facilitated scanning across a breadth of topics via deep engagement with a single feature: by reading every article in the app a user could learn about a variety of inter-related topics about family, children, health and contraception.

> "Yes, I have [used Skata in the past month], but just the articles. A lot of people made comments there [so] it's interesting… [I use Skata because] for me there is a need…so that I won't be left behind. I can keep up with information, so in a conversation with friends the topics will click." – Brebes, Newlywed, Scan

> [I'm interested in] information about this – introduction to relationships within a family. The first thing is the picture [and then] the title, certainly. 'Oh, it describes the closeness between a father and his child.' Then I'd like to see the content in depth…I know about parent-child relationships, but I've never used an application that talks about, for example, child mischief and how it is…So while we understand [this application] is about family planning, this program also helps us build a relationship with our family…When we open this application we don't need to search [specifically] for the topic of father's closeness with his child. Sometimes [in Google] the search term does not quite match and the article will not appear. Here it has the topic already so I just need to scroll a little bit and everything is here already." – Brebes, Spacer, Scan

> [Interviewer: When you first opened the app, you immediately went to an article. Why were interested in that article?] "Well, it may contain more information…it has information and pictures…we gain more knowledge. Sometimes when we deal with our children [we think], 'I really don't understand this kid,' but then the article explains things – 'it's like this, maybe the problem is this, and maybe the barrier is that.' So, we understand more." – East Jakarta, Limiter, Scan

About half of the participants initially motivated to scan were specifically interested in contraception. The contraceptive information feature was an enticing point of engagement, particularly as some noted it would allow them to avoid provider consultation fees.

> "Since this is contraceptive that is inserted into our body or is consumed by us… if we do not consult the doctor beforehand we will be afraid. We're worried the contraception will endanger us, causes cancer or all kinds of problems…If we consult with the doctor, first of all it's quite costly. So, if we can get an explanation from the phone, and if it's truly accurate, it'll be great. We don't need to ask the doctor anymore. Our expense is reduced." - East Jakarta, Limiter, Scan

Since multiple app features covered the topic of contraception, these users were able to fulfill their need for scanning through a wide range of features including the contraceptive information, Ask a Midwife and quiz features. The features with which individuals engaged suggest the gratifications they sought to fulfill through their use of the app. Comparing the features that focused on contraceptives, participants indicated that the quiz offered an additional gratification of entertainment while helping participants learn new information.

> "[The quiz] makes me want to know more. I become curious and curious, because if we answer a question and our answer is incorrect there will be an explanation so our knowledge is expanded. I like [the quiz] more [than the contraceptive information feature] because it gives an explanation. It's fun - it starts with a contraceptive method, followed with an explanation. Like this one: that *coitus* I've never heard of it, but then there's an explanation of it." – Asahan, Spacer, Scan

> [The feature I use] "most often is the quiz. Basically, if I enjoy it then I keep coming back to it…The quiz is direct [whereas] the articles require me to read a lot – too much reading. The quiz questions can be answered right away… I like being able to answer a question, 'Oh this is correct, or no it's not like that…' [The quiz has questions that repeat but I use it] quite often in fact, because I got a question wrong. When I try [the same question] again it is still wrong, so that means I have to keep repeating it in my head, 'oh this is wrong.' Repeat it and it's wrong, repeat again, do it several times. We want to keep on winning." – Brebes, Newlywed, Scan

Many participants initially motivated to scan were interested in information about child development and childcare – resources for raising a healthy, successful child. Multiple app features offered child-related information, such as articles, immunization and school calendars, the educational attainment planning feature, child developmental milestones, and the My Plan feature. The variety of features related to this topic encouraged broad engagement with the app. Participants sought out this information to learn more about childcare, but also to compare the development of their children against a set of standards, to check that their child was developing normally.

> "[I'm interested] particularly in planning for education [of my children]. I'm curious because I have three children…I'd like to know until what age…the cost [to educate them]… For example, in this program about education, I read the information for my first child. I searched for what a 4-year-old can do. The child can say his complete name and can write in capital letters. So that means I have to start teaching my child how to write capital letters." – East Jakarta, Limiter, Scan

Scanners perceived Skata to be an app that covered topics they saw as inter-related: family, health, children and contraception, and they expected the app to cover all of these topics in equal detail. In addition, continuous updates of novel content supported participants' motivation to scan and gratified their desires for information, entertainment, and a need for comparison. Participants voiced frustration, however, when they felt new content was not being added at a pace that met their expectations. When frequency of new content fell short of participants' expectations, users were limited in the depth to which they could engage in features that supported scanning. As a result, the app no longer provided the gratifications they sought or had come to expect. While scanners were interested in using Skata indefinitely, users dissatisfied with the novelty of content were inclined to disengage with the app.

> "The quiz is good…we know things we did not know before. Add questions in the quiz so they don't remain the same old questions and so that we can get new knowledge." – East Jakarta, Spacer, Scan

> "The content stays the same. There have been no changes. I opened it once, then when I opened it again there were no changes at all. Initially I opened the app often. Who knows? There might be new information. Then after a few times I only opened it once a week…Since the articles are not updated, you read them on the first day when you log in and you're done. [When things stay the same] I feel unmotivated. As a result, I will not open this app. Or if [the articles] stay the same, I switch to another part." – Brebes, Limiter, Scan

> "The only thing that appears here is just information that a child of this age will be able to do this and this...I think such information has been shared too frequently and it's already too general. If possible, make it even more specific. Because I'm interested in what age [child] can do what, but the information here is too little. Since the other parts are more detailed, I thought the information [here] would be similar. But it turns out to be too brief here." – Brebes, Spacer, Scan

The one exception to a need for novelty among scanners was a feature that allowed users to self-monitor. A few participants motivated to scan also used Skata to self-monitor, specifically using the menstrual calendar feature. This was the only self-monitoring tool within Skata, and it provided participants with a way to gather information about oneself. Participants seeking to gratify a need to self-monitor exhibited slightly broader feature use within the app as a result, by also using the menstrual calendar. The self-monitoring gratification motivated an intention for periodic re-engagement with the app on a monthly basis.

> "For sure the calendar is usable… [Right now, I use] just the regular calendar. I basically circle the dates…I'd like to have information about the menstrual cycle…I use a condom so I need to know my fertile period." – East Jakarta, Limiter, Scan

> "I have been using a calendar to avoid pregnancy. Now [with Skata] I do not have to rely on a hunch for when I am ovulating and having my period. I will have accurate information. Previously I just used my feeling to avoid sex during my ovulation period…I may leave [Skata] and only log in once in a while. See if there's anything new. Even if it is all the same, I will still go back to the calendar once a month. Yes, to check the calendar, at a minimum one week before my period when I feel uncomfortable, I will go check the calendar. 'When did I get my period last month? Oh yes, my period is almost here.' That's about all." – Brebes, Limiter, Scan

Initial motivation to seek

At the first interview 11 participants in total were motivated to use Skata to seek information in support of making a decision. Specifically, seven participants were interested in seeking information to plan their family's future including determining fertility goals and preparing for children; four participants were motivated to use Skata to seek information supporting their contraceptive decision-making process.

Compared to scanners, seekers had a defined end-goal for their use of Skata: either development of a plan for their future or deciding on a new contraceptive choice. This defined end-goal made their potential length of engagement shorter, as their motivation for using Skata could eventually be satisfied without a need for continuous infusions of novel content. In addition, seekers' pattern of feature use within Skata was much narrower than that of scanners, as seekers' use of the app was goal-oriented primarily to gratify a need for surveillance and information gathering. Thus, a small set of features was able to satisfy their goals.

<u>Seeking to plan for the future</u>

Participants initially motivated to use Skata to plan their future were mostly newlyweds. The My Plan feature appealed most to these participants and was the main feature they intended to return to when using Skata. This feature allowed participants to envision what they would like their family to look like, and how to prepare for that future. The feature prompted participants to make more detailed plans and preparations for their future, including considering the cost of education, preparing for children's emotional milestones, and life as a couple through older age. Participants planning their future used the feature as a life simulator: altering the data they entered to see how changing their fertility goals might affect their life over the long-term. As described by participants seeking to plan their future, the end-goal for achieving behavior change was making as detailed a life plan as possible given the tools available in the app. As a result, adequate engagement to satisfy their goals was reflected in a lengthy session or repeated use of planning features.

> "I feel as if we get information about our life at certain ages…I have thought about [planning my family], but never up to this much detail... It's detailed and even includes the ages, etc…[Our] plan is there, but it's not that detailed all the way until we are 70 years old. All this time we just planned to have 2 children, if possible a boy and a girl, then we make plans until they go to college. That's all." – Asahan, Newlywed, Seek(Plan)

> "I want the information to be saved – the results of planning. The one where it says I want to have the first child at age A. But if I change it to age B, the result will change. This paragraph of the My Plan summary is some kind of financial planning [calculates whether user will pay double school fees, depending on the spacing of children]. It's different for the different conditions, so it can be used for comparison." – East Jakarta, Newlywed, Seek(Plan)

> "I've tried [My Plan] several times. I tried the scenario with 2 children, then with 3 children in a certain year, etc. Well I'm simulating the planning. This year, that year, what if I add this, what if I have another child, those things." – Brebes, Spacer, Seek(Plan)

<u>Seeking for making contraceptive decisions</u>

Only four participants were initially motivated to use Skata to seek information specifically to make a contraceptive decision, three of whom wanted to limit their pregnancies. While there were many scanners who were interested in contraceptive information, only a few participants we interviewed started out in the midst of a contraceptive decision. For these few women, similar to scanners, Skata information offered the advantages of avoiding unsatisfying encounters with providers for the purpose of information-seeking and having a central repository for information to make information-seeking more pleasant, self-directed and efficient.

> "I'm satisfied reading the information [about contraceptives in SKATA] ...consulting with a midwife is sometimes awful. One time after I had my implant removed, I

> consulted with a midwife but…her answers were brief. I wasn't satisfied, there's no way she would explain things like in here, she was very brief." – Asahan, Limiter, Seek(FP)

> "I prefer this app because it's complete. Everything is visible already and I can just choose what I want. In Google I'll have to click on each search result." – Asahan, Newlywed, Seek(Plan)

When making a contraceptive decision, participants followed a series of steps and Skata only played a small role in helping participants to progress through their decision-making process. First, participants compared the information in the contraceptive information section with their personal experience. Given the wide array of methods for which information was available, participants often started by reading about methods they had used or were currently using, seeking information on familiar methods and assessing whether the information provided was similar enough to their knowledge or experience to not raise any doubts about the credibility of the app.

> "Oh yes, for a tubectomy a doctor told me that you can have the tube cut off or tied, and afterwards if there is contact the woman can become pregnant again. Oh, here it says it is permanent – sterile. So, what the doctor told me may be the semi-permanent one. What I know is that the procedure can be to either tie it up, or to cut it." – East Jakarta, Spacer, Seek(FP)

> "Yes, I've received a leaflet [about implants] and the points are similar. Though this app gives more information." – Brebes, Limiter, Seek(FP)

Participants seeking contraceptive decision-support next focused on reading about the method(s) that they were considering as a means of narrowing their selection. In the steps of comparing information to one's own experience and seeking to narrow as part of making a contraceptive decision, participants described engaging primarily with the contraceptive information feature, and to a lesser extent with the Ask a Midwife feature, both for the purposes of surveillance, or information-gathering. Engagement was directed to learning about specific pre-selected methods. So, in comparison to scanners, seekers were less broad in their engagement across features, as they did not intend to read through all features that contained contraceptive information. Seekers' engagement was also less deep than scanners, as even within the contraceptive information feature alone seekers did not intend to read about every contraceptive method.

> "I discussed Skata with my colleague at school. [She uses] injectables, same as me. [After she saw Skata's Contraceptive Information section] she'd like to use IUD, that's what she said. She's been interested in an IUD for quite some time. The she read [about it] in Skata. 'Oh, now I know,' [she said] and she wants it even more." – Brebes, Spacer, Scan

> "Quite a lot of people use implant actually and initially I found out from people, then I read in Skata and it became clearer…in 'My Contraception,' there is information on implants…It's here, the advantages are it's easy to stop using this method and it doesn't leave a mark. The insertion is easy." – Asahan, Spacer, Seek(FP)

Finally, participants sought support outside of Skata to gather experiential information about methods they were considering and develop greater self-efficacy to adopt a new method. Skata did not provide the means to gratify a need for experiential information or allow participants the ability to build relationships with others who had made similar contraceptive decisions. As a result, participants described patterns of use where they engaged deeply with content on the method(s) they were considering followed by a period of disengagement before making a contraceptive decision and possibly taking action.

> "As far as I know IUD insertion is scary, but after I read [the SKATA information], it doesn't seem as scary as I had imagined ...[the app has] information about proper insertion. Basically, that is what the midwife told me - she will insert it and we have to obey her advice, not do this, not do that, just obey those, and the important thing is maintain our health…The midwife recommended me to use IUD because it's safer and does not have any effect on my body. It's also more economical, that's what the midwife told me…people I know have a good experience with it. My sister uses IUD and has a positive experience." – Asahan, Spacer, Seek(FP)

> "[At follow-up] I'm using [an implant] ...Before I read Skata I asked a friend, 'does this method have any side effects? There must be something about the method that scares people.'...After I read Skata, 'Oh it turns out it's like this.' The insertion procedure, the effects. Yes, [Skata] encouraged me...For me it's not enough. I had to ask around... I watched the procedure being done to my friend… I could see the insertion procedure in-person. The device also…Indeed, I learned to be brave. I learned to have courage. I watched the insertion process – I truly witnessed it, you know? So it was truly like this – I saw the midwife insert it...I asked around about how people feel when the device is inserted, do they feel comfortable? I asked friends who have used that method, particularly those who have used it three times… [I talked to] my friends from the *arisan* [women's savings group] [about implants] and a lot of them already use the method. 'Yes, it's quite comfortable indeed,' they said that. So I became interested as well...My husband is also supportive – praise God." – Brebes, Limiter, Seek(FP)

From this pattern of disengagement while seeking, we see that engagement with the app does not necessarily equate to engagement with the behavior change topic. If a gratification cannot be satisfied within the app, participants communicate through other means to satisfy their needs for making a decision. Interpersonal communication can similarly be seen as playing an important role in influencing motivation to use Skata and influencing the length of Skata engagement across users of various motivations.

The role of sharing on motivation

Sharing, or interpersonal communication about Skata topics, provided participants with a reason to extend their period of engagement with Skata – rather than scanning or seeking for oneself, participants who shared discussed using Skata to benefit others. This motivation to share and subsequently engage with Skata for the purpose of building relationships with others seems fitting in a collectivist culture, as Indonesia has been described. The deep-rooted "duty to make influential others' lives easier" may manifest itself in the desire to share about Skata and subsequently to be motivated to use Skata to aid in efforts to share information with others.

Sharing among participants with no initial motivation

One participant with no initial motivation to use Skata shared the app with friends. As she re-counted sharing with friends she described Skata as a valuable resource that she was able to provide to others. While she herself had no motivation to use the app, her engagement with the app was extended due to a motivation to share the app and benefit others.

> "We [my friends and I] typically don't enjoy reading books, so having this application on a mobile phone is great. One friend of mine just got married, another friend became pregnant after 6 years; they're all thrilled to know this app. They can plan when to get pregnant again, what is next, what contraceptive to use…Yes, so I focused on My Plan and Contraception." - Brebes, Spacer, No motivation

Sharing among scanning participants

Five of the 15 participants who used Skata for scanning purposes at follow-up noted that they were also able to share information with family members and friends as a result of using

Skata. Generally, participants simply shared the fact that Skata exists, not focusing on any specific feature within the app. Sharing about Skata's existence did not seem engender much discussion or influence a user's engagement. So, although these participants received an unexpected gratification of building offline relationships as a result of their own engagement with Skata, the relationship building was minimal.

> "I think [my male colleague's] wife is curious about this app too – perhaps the husband told her [about it]. She called me yesterday, 'What is it – I saw your text message [about] Skata? What is it like?' I told her…I think she wants to know about birth control pills. She's taking pills now and she's becoming fat. I told her, '[Skata] is quite complete here *Ibu* [ma'am]. Just go ahead and read it – all you need is just to read this.'" – Asahan, Newlywed, Scan

> "I was trying to open Skata through one of [my friends'] phones. So, they asked me what it is, and I told them that it's an app about family, contraception… We were just chatting, and I said try opening the application. I don't know [if she looked at the app], but she said it's good. That's all." – Brebes, Limiter, Scan

A few participants, however, shared a particular feature of the app and were thus able to open up a space for discussion of app content. Sharing helped scanning participants experience a new gratification of relationship building, as use of Skata afforded them the opportunity to provide entertainment and inspire conversation. In addition, scanning participants who shared experienced a new motivation for Skata use – continued scanning for the benefit of others. Similar to participants with no motivation, scanners who shared may have extended their engagement with the app due to this collectivist-oriented motivation.

> "I have a few friends and I told them to install Skata. There were three office colleagues. We chatted [about the quiz]. The quiz is fun – it can be made into something humorous. For example, some of us answer based on our experience, and then sometimes our answer is wrong. So we all laugh together." – Brebes, Limiter, Scan

> "I've even uploaded stuff to Facebook – an article - the one about early marriage and the one with a picture of a father and young child [about father-son relationships]. [I shared it] so that my friends know how important it is for a father to be close to his children…Three or four people, they gave a 'like.' I wanted a lot of comments so that I could provide a response and continue further." – Brebes, Spacer, Scan

Participants who shared a specific app feature and elicited discussion may have experienced more meaningful relationship building than those who share simply about the existence of Skata. The richer sharing experience seemed to offer potential for encouraging prolonged app engagement.

On the other hand, feature-specific sharing that did not elicit discussion did not dissuade engagement, but it may have brought the desire for relationship building around family and health-related topics to the forefront of users' minds. For example, participants struggled to elicit discussion with their husbands about what they read in Skata. While lack of reaction did not change participants' intrinsic motivations for engaging with Skata, it reinforced the perception that an app about family, health and contraception is gendered and more relevant to women. Within the couple, participants who shared did not talk about experiencing a new motivation to use Skata for the benefit of their husbands.

> "Men would not read [Skata articles] unless the wife lays it in front of him [and says], 'It's like this. This is a good article, it's this and this and this.' So, we have to tell him first, start a dialogue first and tell him 'I read here [in Skata] this and that.'…My husband did not pay that much attention. He said, 'Oh yes,' that's all. Sometimes this kind of thing is a women's thing. Contraception is mostly for women, so we have to take care of it on our own. Men are not that interested in it." - East Jakarta, Limiter, Scan

> "[My husband] said that if this app gives a lot of knowledge, then I should read it diligently so that I can understand things better. I can increase my knowledge. It's better than browsing for unimportant stuff. [When I shared information from an article with my husband] he was just quiet. He was thinking, I think, but he didn't say anything. Maybe he thought, 'this is a female thing,' maybe." – Asahan, Spacer, Scan

> "I had told him once; this app is this-this-this. I didn't tell him about every article, so just a little bit here and there. Because he's also busy, so he never said, 'let me see.' He hasn't said that yet. If he asks to see [Skata], it'll be better." – Asahan, Spacer, Scan

<u>Sharing among seeking participants</u>

Seekers who achieved behavior changes of creating a plan for their future or adopting a new contraceptive method had a natural inclination to share their experiences. This desire to share is similar to what Ziebland et al. 2016 describe in patient experience websites where the typical engagement loop ends with users trying to add their own voice and contribute their experiences to ensure others like them will find the resource helpful in the future.

Since Skata did not offer many in-app features that facilitated experience sharing, seekers talked about interpersonal communication as the best outlet for sharing with others. Successful seekers advocated about the importance of future planning and learning about contraception, and they promoted the app as a helpful tool for learning, planning and contraceptive decision-making. Through sharing, these participants were able to build relationships by bringing others entertainment and new factual information paired with their own experiential information. While participants connected to a social group had an outlet for sharing, some participants faced with a dearth of in-app sharing features disengaged from the app despite remaining engaged with Skata topics.

> "[When I share about Skata in a gathering] I discuss the quiz. I start with a question to provoke a response. For example, I ask them 'Can an implant become loose? Where is it placed?' I pose a question…I kind of promoted this [implant] too…The cadre also asked me to help introduce the device; I was the model… [the audience] asked, 'were you afraid when it was inserted?' [I said] 'Yes there was fear.' [They asked] 'are you confident and firm [in your decision] about this method? Who knows, maybe midway you'll ask to have it removed.' [I said] 'Yes, I am firm with my decision…meaning I will continue this method for three years.' …[Interviewer: Would you be willing to share your testimony on social media?] Go ahead, I may be able to do it. It's also sharing of experience." – Brebes, Limiter, Seek(FP)

> "[My Plan] is basically a simulation tool. Regarding planning we indeed have made plans … we have planned the budget in more detail [than Skata]…It'll be interesting [to have more detail about expenses in the app], since sometimes people need an illustration about how high the expense will be, so that they can start preparing from now on, and it can be a consideration for both the husband and wife. My husband is someone who loves to plan, and he's been doing the calculation…[he] saves his plan in a file. When he wants to make a plan, he usually will do a presentation and I'm supposed to listen to him… hahaha." – Brebes, Newlywed, Seek(Plan)

Discussion

Interviews in this study reveal relationships between motivations for DBCI use, resulting patterns of feature-specific use within a DBCI, and cycles of disengagement and re-engagement facilitated by experience sharing. Motivations for DBCI use are essential to understand, as they help to determine metrics of success in achieving behavior change goals as a result of engagement – the goal of engagement varies depending on the user's motivation for using the intervention.

Success of DBCIs is traditionally measured by percent of users who achieve ‘adequate engagement,’ assuming all users are seeking support to make an immediate behavior change. However, the threshold for ‘adequate’ engagement may vary depending on motivation for engagement. Participants with a motivation for scanning report use of a broad array of features, especially if topics they are interested in are woven into multiple features of the app. Since the end goal of scanners is simply to survey information, programs need not specify an ‘adequate’ threshold for engagement as these participants do not intend to make any particular behavior change beyond knowledge acquisition. Scanners’ engagement can be sustained through continuous updates of novel content distributed across the range of topics covered in the app, and by servicing gratifications beyond surveillance, such as providing features that allow self-monitoring or provide entertainment. In contrast to scanners, participants motivated to seek typically exhibit deep, repeated engagement with specific features that support a decision-making goal. ‘Adequate engagement’ can be more clearly defined as engagement with the app to a point that facilitates behavior change.

In examining the experiences of seekers using the Skata app, we saw that engagement followed a process of gathering information and comparing information provided to personal plans or experience. These steps happened with the assistance of Skata. However, Skata features did not offer participants the ability to satisfy the next steps in their behavior change process. Participants sought to build efficacy for their potential decisions by gathering the experiences of others and sought to build relationships with others who had undergone a similar seeking process. Finally, they sought to share their experiences of change. Prior to assessing ‘adequate engagement’ for participants motivated to seek support for making behavioral changes, we realize that the app must provide features that facilitate the full process of behavior change. If users disengage from the DBCI but continue to engage with the topic it is a sign that programmatic adjustments could be made to offer a more comprehensive communications experience within the intervention.

In addition, researchers must consider the role of interpersonal communication in measuring behavior change that results from engagement with a DBCI. Rather than attributing behavior change solely to achieving an adequate level of engagement with the DBCI, a more conservative measurement model would include measurement of interpersonal communication resulting from engagement with the DBCI. This construct may be particularly salient in collectivist contexts where there is high normative influence on individual actions.

The findings from this study emphasized the role of sharing, or interpersonal communication, on increasing engagement and enhancing behavior change. Through sharing of content, scanning participants developed a new motivation to engage with the DBCI, for the sake of informing others. Discussion about Skata content seemed to encourage sustained app engagement because in addition to the user's internal motivation to engage with Skata she experienced external motivation driven by the desire to build relationships with others. In contrast, lack of discussion did not seem to influence intention to engage with Skata but limited potential for Skata engagement to the users' internal motivations. Among seekers, participants who experienced change naturally sought opportunities to share their stories of change resulting from Skata use. A gratification to build relationships, coupled with the collectivist context in which emphasis is placed on making influential others' lives easier, encouraged participants to share their experiences through any means available. By incorporating features that allow in-app sharing such as user-generated testimonials, a DBCI program can harness seeking users' natural inclination to share experiences, and possibly alleviate the need for future users to disengage from the app as they seek experiential information. Seeking participants could experience a new motivation to engage with the DBCI after behavior change for the purpose of sharing their experiences with others, thereby lengthening their engagement with the app.

These findings prompt further questions about the role of interpersonal communication in digital interventions for behavior change. How does sharing influence engagement with the DBCI, the topics covered in the DBCI and an individual's behavior? Is there potential for sharing to inspire a shift in a user's motivations for DBCI use? For example, when scanners shared Skata and observed others using the app to make fertility goal plans or contraceptive decisions, did this modeling prompt scanners to reflect on their own need to seek information? More research is needed to understand how sharing affects engagement and behavior change, and whether sharing facilitates DBCI users to shift from scanning to seeking states.

Limitations

This study had some limitations to understanding the connection between motivation and engagement, and the role of sharing in shifting motivations for DBCI use. First, participants' initial motivations for use of the Skata application were inferred from their comments about which features they intended to return to within the one-month study period. Participants did not always directly state their initial motivation for using the app, and future research should more directly assess this factor. Second, given that participants knew there would be two rounds of interviews in this study, they may have been more compelled to find a motivation for using the app in the study period than if there was no research study introducing this app to them. Third, the one-month study period may have been too short to capture participants' evolutions in motivation and patterns of re-engagement with the DBCI, particularly among participants with no initial motivation to use the intervention. The appropriate study period for observing relationships between engagement and behavior change may also vary depending on the health topic, so these insights may have less applicability outside of reproductive health. And finally, insights about the role of sharing in facilitating engagement may be specific to contexts in which decisions are made more collectively rather than being individually driven.

Despite its limitations, this study is valuable for connecting motivation for use with patterns of engagement to guide programmatic refinement of DBCIs. In addition, the emphasis on the role of sharing helps to refine measurement models that seek to assess how DBCI engagement leads to behavior change.

Conclusion

Motivation is an important determinant of engagement patterns with DBCIs. Users motivated to scan or gather information may have no reason to disengage if features are updated with new content across an array of inter-related topics. Their engagement could ideally be deep exploration of features that gratify a need for information and/or entertainment. Users motivated to make a decision or behavior change may only engage for a brief period of time, with the depth of engagement limited to a small set of features that facilitate decision-making. Understanding users' process of decision-making may help in identifying additional features to add to the DBCI that can deepen users' engagement. Finally, in collectivist contexts, disengagement may not be the norm after use of a DBCI for achieving change. Rather, features that facilitate sharing may help to sustain user engagement among those who achieved behavior change as a result of DBCI use.

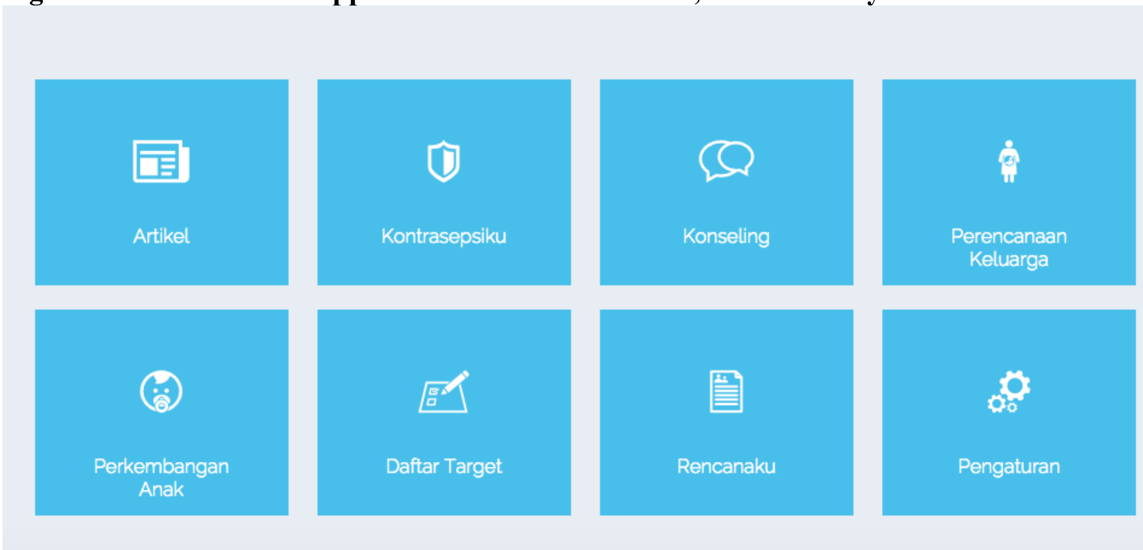
Table 5.1: Interview Participants

Interview districts	Respondents	# persons, Interview 1	# persons, Interview 2
1) East Jakarta	Newlywed women, parity 0		
	• FP users	0	0
	• Non-FP users	2	1
	Married women, parity 1+, interested in spacing		
	• FP users	2	2
	• Non-FP users	2	2
	Married women, parity 1+, interested in limiting		
	• FP users	2	2
	• Non-FP users	2	2
2) Brebes	Newlywed women, parity 0		
	• FP users	2	2
	• Non-FP users	2	2
	• Married women, parity 1+, interested in spacing		
	• FP users	2	2
	• Non-FP users	2	2
	Married women, parity 1+, interested in limiting		
	• FP users	2	2
	• Non-FP users	2	2
3) Asahan	Newlywed women, parity 0		
	• FP users	1	1
	• Non-FP users	3	2
	Married women, parity 1+, interested in spacing		
	• FP users	2	1
	• Non-FP users	3	3
	Married women, parity 1+, interested in limiting		
	• FP users	2	2
	• Non-FP users	1	1
TOTAL		**34**	**31**

Table 5.2: Number of participants, comparing life stage & initial motivation for using Skata

Life stage	Initial motivation for using Skata (n = 34 participants)			
	Scanning	Seeking		No current motivation
		Planning for the future	Contraceptive decision-making	
Newlywed	4	6	--	--
Spacing	8	1	1	2
Limiting	8	--	3	1
Total	**20**	**7**	**4**	**3**

Figure 5.1: Skata mobile application main menu screen, circa January 2016



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Chapter 6: Discussion

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Chapter 6: Discussion

Summary of Findings

Research Aim 1: Understand how "engagement" is conceptualized and propose a system for operationalization

Chapter 3 presented a concept explication to clarify the concept of engagement with DBCIs and propose a matching measure. The concept explication was informed by a review conducted in 2016-2017 including literature from the PubMed and Communication and Mass Media Complete databases and supplemented by grey literature recommended by experts and included in online databases such as the mHealth evidence database and the Human Computer Interaction Bibliography. A total of six studies were used to inform the conceptualization of engagement with DBCIs, and 69 studies were used to catalogue operationalizations of engagement with DBCIs.

The concept of engagement was defined as consisting of three dimensions: cognitive engagement, emotional engagement and behavioral engagement. The study further focused on behavioral engagement, defined as the interaction between the user and the engagement object. Four phases of behavioral engagement were described in the literature: 1) the point of engagement, 2) a period of sustained engagement, 3) disengagement, and 4) re-engagement. Operationalization focused on identifying a suite of measures to capture these phases of behavioral engagement with DBCIs. An Extended Engagement Index (EEI) was proposed, building off of the modified Engagement Index (EI) used by Taki et al 2017, to robustly measure the concept of engagement, including all dimensions and phases, with particular emphasis placed on behavioral engagement. The EEI included the five subscales from Taki et al 2017's EI: click depth, loyalty, interaction, recency, and feedback. Additional subscales were proposed to include measures from the original EI proposed by Peterson and Carrabis 2008 and to measure the full spectrum of dimensions and phases of engagement as described in the concept explication.

Specifically, additional measures were proposed to assess duration of DBCI use, cognitive engagement related to awareness and acceptability of the DBCI among potential users, breadth of features used, and use of features specifically targeting the behavior of interest. Finally, recommendations about the length of study were proposed to help standardize use of the EEI as an evaluation tool across DBCI studies.

<u>Research Aim 2:</u> Apply the operationalized engagement measure to identify factors correlated with engagement in Skata

Chapter 4 applied the EEI to the Skata mobile application (app) and website in Indonesia. In applying the EEI to real data, we were able to assess the scale's reliability and validity against a typical measure of engagement, length of DBCI use. The EEI was also utilized as an outcome to assess factors that predicted engagement in Skata. Data were collected from the Skata app and website exhaust, the data created as a byproduct of app/website use, over a period of five months following Skata's launch, from April – August 2016. Data were restricted to adult male and female users who registered with Skata and visited Skata at least once. The total sample of the study was 15,909 registered users.

An EEI score was calculated for each user using six subscales: click depth, duration, loyalty, interaction, recency, and feature breadth. The score was calculated using three time periods: the first visit, visits 2-3, and visits 4 and beyond.

Similar results were obtained comparing demographic and Skata access features over a dichotomized standardized EEI score and a dichotomized length of use measure. Specifically, more engaged users were more likely to be female, newly married under age 35 or spacing or limiting children, and access Skata through the app only or a combination of the app and website. The distribution of the standardized EEI scores more closely approximated a normal distribution than length of use and had strong internal consistency (Chronbach's Alpha = .8630).

An Exploratory Factor Analysis was conducted to determine if there were any underlying patterns to Skata page use in visits 2 and beyond. Five factors were identified, representing: 1) seeking for the purpose of contraceptive decision making, 2) scanning with a focus on child education, 3) scanning with a focus on contraception, 4) scanning and seeking to plan for the family's future, and 5) time management. Factor scores for each of the five factors were calculated per user.

Regression analyses were performed to identify demographic, Skata access, and psychographic factors that predict Skata engagement. A final multivariate regression model concluded that users were significantly more engaged with Skata if they were under age 35 and spacing children or were limiting childbearing and if they were motivated to use Skata for any of the four factors related to seeking and scanning motivations. Controlling for demographic and psychographic characteristics, users were significantly less engaged with Skata if they only accessed Skata through the website.

<u>Research Aim 3:</u> Understand the Skata user's engagement experience

Chapter 5 qualitatively explored the experience of engagement with Skata in Indonesia. Data came from two rounds of structured interviews with 34 women representing three family planning life stages: newlywed, spacing children and limiting children. Interviews were conducted in three locations: East Jakarta and Brebes in Java, and Asahan in North Sumatra. Each participant was interviewed twice, with interviews one month apart. The first interview was used to introduce Skata and assess usability and initial expectations, while the second interview focused on how participants used and discussed the app in their daily life.

Interviews revealed that rather than life stage, motivations to use Skata were the most useful way of comparing experiences of using the app across participants. Women who were motivated to use Skata in order to scan for information used a broad array of features and their interest was sustained when they perceived the content to be novel, continuously updated, and servicing needs beyond information provision to include self-monitoring and entertainment. In contrast, users motivated to use Skata to seek information for planning their family or making a contraceptive decision exhibited deep, repeated engagement with a small subset of Skata features that supported their decision-making goal. Interpersonal communication played a significant mediating role between DBCI engagement and behavior change, with participants describing the ways in which they built efficacy to make a family planning or contraceptive method decision by gathering experiences of others and building relationships with people who had undergone a similar change. Interpersonal communication also facilitated extended Skata engagement for scanning participants, by giving them a reason to continue to scan for the benefit of others. This qualitative exploration led to refinement of the DBCI measurement model, suggesting that engagement with DBCIs can indirectly affect behavior through a reciprocal relationship between interpersonal communication and engagement with the health topic.

Conclusions

Taken as a whole, this thesis offers a series of measurement models specific to digital behavior change interventions (DBCIs) to comprehensively measure the social and ecological factors that influence engagement with DBCIs, and in turn, how engagement with DBCIs relates to behavior change. The research addresses critical gaps in the literature about a clear and complete definition of engagement with DBCIs and proposes a systematic, robust measure that aligns with the concept of engagement and allows for comparison of engagement across DBCIs. This study also acknowledges the boundaries of how much DBCIs may affect behavior change and proposes an indirect pathway through which DBCIs may act on behavior.

As digital technologies continue to evolve, the field of digital health may need to expand measures of engagement to maintain flexibility of the metrics to account for new ways in which humans interact and engage with technology. The EEI proposed in this study contains nine subscales with formulas that allow for adjustment to suit a variety of interventions. However, using the z-score standardized approach to calculating the overall index allows additional subscales to be added to the EEI if new technology features warrant doing so. For example, the duration subscale currently accounts for average duration per visit, but with interventions that include video features based on social learning theory it is possible to add an additional subscale specific to measuring average duration of video viewership and target measurement of engagement to a unique theoretical construct. By acknowledging any deviations from the original EEI and reporting on results of each subscale of the EEI, DBCI programs can continue to compare engagement measures and make inferences about how intervention features may affect engagement even as technology changes.

This study differentiated factors that *influence* engagement from *measures of* engagement, to more clearly define engagement itself. Presenting the landscape of factors that influence engagement, this study lays out a vast research agenda for DBCI evaluation and offers a robust outcome variable to use in these evaluations. In addition, this study highlights several individual and interpersonal factors that influence and are influenced by engagement with DBCIs – motivations for use and interpersonal communication.

This incorporation of reciprocal determinism between interpersonal communication and engagement adds nuance to the ways in which researchers may evaluate DBCI effects in the future and underscores how decision-making processes take place over time. The consideration of these individual and interpersonal factors also prompts social and behavior change programmers to think differently about DBCI target audiences. While audiences motivated to seek information may be a primary audience of interest to target, the value added in targeting scanning audiences may be that they help to amplify the messages in a DBCI and can potentially catalyze information seeking when it is relevant to DBCI users' lives. The feedback loop between engagement with DBCIs, interpersonal communication, engagement with the topic and motivations for DBCI use helps to describe the way in which individuals have communication needs that evolve over time and the behavioral impact of communication interventions may need to be measured over a long-term window.

In concert with one another, the three manuscripts in this thesis triangulate on the concept of engagement with DBCI, examining the concept through three different approaches. First, a concept explication is used to clarify the concept. Then, qualitative analysis is used to understand how the concept can be operationalized and applied. And finally, a qualitative study explores how behavioral engagement with DBCIs can be further enhanced by collecting data external to app and website data exhaust. The three studies together converge on the importance of engagement with DBCIs as a mechanism through which DBCI effectiveness outcomes vary.

Limitations

This study has some overall limitations. The primarily limitation of this study is that we did not overtly measure behavior change to assess the relationship between DBCI engagement and behavioral outcomes. While the study captures some anecdotal evidence of behavior change through qualitative inquiry, outcome measurement was not part of the design of the Skata mobile application. The decision not to measure behavior was made intentionally. Skata was designed as an intervention, not a research mechanism. Therefore, since inputting and periodically updating family planning and contraceptive behaviors was not part of the app features, no data was captured on these indicators via data exhaust. The research team decided not to include user survey functionality into Skata, because doing so could change the natural interaction of the user with the DBCI and would pose burden on DBCI users to participate in research activities.

The engagement concept defined in this study was informed by literature from a limited set of disciplines. Specifically, the literature consulted covered the fields of public health, digital health, communication, and computer science. Additional disciples such as psychology, marketing and broad social science literature databases may have offered additional studies that would have been relevant to include in the concept explication, and thus may have further extended the number of subscales operationalized within the EEI. Furthermore, there is a rich literature on the concept of involvement in the field of marketing that focuses on product and issue involvement. The concepts of involvement and engagement, which is more specific to digital interventions, may be highly complementary. By exploring literature in marketing disciplines and under the topic of involvement, this research may have been able to connect DBCI engagement with a much larger field of research. Instead, this examination was limited to a narrower range of disciplines that pertain more closely to public health.

This study applied measures of engagement and explored engagement experiences with a single DBCI, only in Indonesia. This presents the limitation that the EEI was not validated across a range of DBCIs that vary in architecture and span a variety of health topics. Skata, with its open menu, nested page architecture and focus on family planning may have been particularly well suited to measuring phenomena such as click depth, duration, loyalty, recency, interaction and feature breadth. An intervention with a more modular architecture may affect these phenomena differently, perhaps placing higher emphasis of the effect of click depth on overall engagement as the user would have to pass from one module to the next to engage further with the DBCI. An intervention focused on a different topic area may have fewer types of features, in which case breadth may not be a salient measure of engagement. In addition, the Indonesian context may be qualitatively different from other contexts in shaping engagement. Specifically, Indonesia is a collectivist culture (Hofstede Insights, accessed November 2017) in which social motivations for engagement with DBCIs may be particularly salient. This indirect pathway for DBCIs to affect behavior change may be less relevant in other cultural contexts.

Engagement is discussed as a multi-dimensional, multi-phase phenomenon; however, this study focuses on behavioral engagement primarily during the period of engagement. Engagement dimensions include cognitive, emotional and behavioral components. While there is some discussion of measuring cognitive and emotional engagement in the EEI, Skata data exhaust only provided the means to measure behavioral engagement. The concept of engagement implies a time element, and this study limited the period of study to five months (quantitatively) and one month (qualitatively). These time limits on engagement constrained our ability to measure some dimensions of engagement, specifically re-engagement. The analyses in this study focus on the period of engagement as little data was captured through data exhaust to document the point of engagement, and qualitative exploration about the point of engagement captured through usability interviews were not deemed relevant to include in this dissertation.

A DrPH Dissertation – Implications for Skata

A unique strength of this dissertation is the way it strives to integrate the objectives of a DrPH degree into thesis-level research. DrPH dissertations at the Johns Hopkins Bloomberg School of Public Health (JHSPH) are expected to be "practice-oriented" and "expose students to the whole cycle of identifying problems, collecting and analyzing data and developing public health solutions…to address high-level and complex public health problems." (JHSPH DrPH Program, accessed February 2018). Research for this thesis was practice-oriented, conducted within the context of a real, on-going public health intervention. Data collection was equally practice-oriented. Rather than designing an experimental study and administering surveys, the research team consciously chose methods that would be unobtrusive for the majority of Skata users. These decisions were made so as not to disrupt the effects of the intervention program for the purposes of conducting research.

In addition, while contributing to high-level areas of inquiry on engagement with DBCIs, this research helped to shape the next iteration of the Skata mobile application in Indonesia. Through usability testing we uncovered several insights that led to refinements and redesign of the app and website. Specifically, interviews helped us understand the expectations of users for greater novelty of content. Whereas new articles had been added at a pace of 2-3 per month based off of Internet scraping for relevant content that could be translated to Bahasa Indonesia, the program team realized they needed to increase the frequency of updates to 1-2 articles per week. As a result, two staff members were hired to write new content in the form of articles and social media posts. The latest articles are now featured prominently on the landing page of the app and website, and social media assets such as Skata's Facebook, Instagram and Twitter accounts have been integrated into the website to make new content more visible (see Appendix

10 for a list of Skata digital assets). In response to usability testing comments about an expectation for greater interactivity, especially in the 'Ask a Midwife' feature, the program team started to conduct live interviews and question-and-answer sessions through Skata social media, which are now integrated into the website. This refinement allows the program team to be responsive to feedback while working within their staffing and financial resource constraints. The Skata app and website aesthetics and feature offerings were also adjusted in response to usability testing and analysis of data exhaust (see Appendix 11 for screen captures of Skata version 2 from April 2016, used for testing in this research, and Skata version 4 from February 2018, refined to reflect research findings). For example, the architecture of Skata was changed to eliminate the nested menus that users had to navigate, so that all features available in Skata are now visible from the main landing page. Features were also eliminated, including the to do lists which had showed no influence on engagement in the data exhaust and generated little enthusiasm during interviews. Popular features are now contextualized where necessary per usability interviews, such as adding Standard Days Method guidance to the menstrual calendar to clarify how to use the feature as a natural contraceptive method. Finally, gaming literature on engagement was applied (see Appendix 1 for Octalysis framework) to incentivize Skata loyalty by creating a framework of quiz 'modules' to achieve mastery on a range of subjects related to family planning and contraception.

The hallmark of a DrPH dissertation is its orientation towards practice-based research. This thesis presents the findings of my research at a high-level, but those findings were gleaned through a process rooted in practice and identified through multiple rounds of stakeholder sharing. The initial usability testing and data exhaust research conducted for this dissertation informed revisions to the Skata app and website. Findings were then abstracted to inform DBCI work more broadly – though multiple rounds of feedback from staff at the Johns Hopkins Center for Communication Programs (CCP). Results dissemination meetings were held immediately after each round of qualitative data collection, and subsequently as the lead author analyzed the data. CCP feedback on how study results helped to shape the next round of Skata program planning informed the development of discussion sections for the manuscripts included in this thesis.

Implications for Public Health Practice

This dissertation has several implications that may merit consideration for public health practice and digital health writ large. This study created a framework for evaluating the effects of DBCIs on behavior, which will allow programs to consider how social and contextual determinants influence the success of DBCI programs. By understanding structural influences on DBCI engagement, program staff are given the impetus to liaise with ministries involved in technology infrastructure, as well as formal social structures (e.g., workplaces, formal social groups) that may influence DBCI use.

The development of the EEI has practical implications. By providing a more robust engagement outcome measure than the traditional length of use outcome, we offer a metric that can be analyzed in rapid A/B testing of DBCI features. Since the EEI has subscales that can be measured over a single visit rather than being reliant on measurement over an extended time period, these indicators can be used to extrapolate on how feature adjustments may affect longer-term DBCI engagement.

The practical implications of this research on DBCIs also bring up an ethical issue for consideration within social and behavior change programming. By understanding the factors that predict engagement through data exhaust, we were able to enhance the psychographic profiles of DBCI users for the Skata program. We better understood the specific app and website features and types of content that the program should expand upon to enhance engagement. However, by changing a DBCI in response to data exhaust results, we narrow the audience who may find the intervention compelling and useful. Audiences who had access to and interest in the DBCI dictate how it evolves, and those who did not have access or were not compelled by the initial content are not captured through data exhaust. The unintended result of using data exhaust to inform DBCI refinement may be that users with limited access or interest may become more alienated from a DBCI as its content is revised, because their voices are not used to inform the revision process. This study tried to avoid these unintended negative consequences by triangulating findings from data exhaust findings with qualitative findings to allow for a more balanced sample of Skata users representing a range of socioeconomic background, fertility intentions and potential motivations to use the DBCI. The implication of this triangulation approach to public health practice is that multiple methods may be required to ensure a balanced sample and inform changes to DBCIs so as to not create a greater divide between those who are being serviced and those the program intends to serve.

Finally, this dissertation has broad application outside of public health, to the fields of digital advertising, marketing and communications. Engagement describes the dynamic interface between user, technology and content. While this thesis applied the EEI to a public health DBCI and proposed an indirect pathway through which DBCIs may affect behavior change in the context of family planning decision-making, these tools and frameworks could be tested and used in any digital program that aims to change behavior, regardless of whether the behavior is health-related.

References

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Appendices

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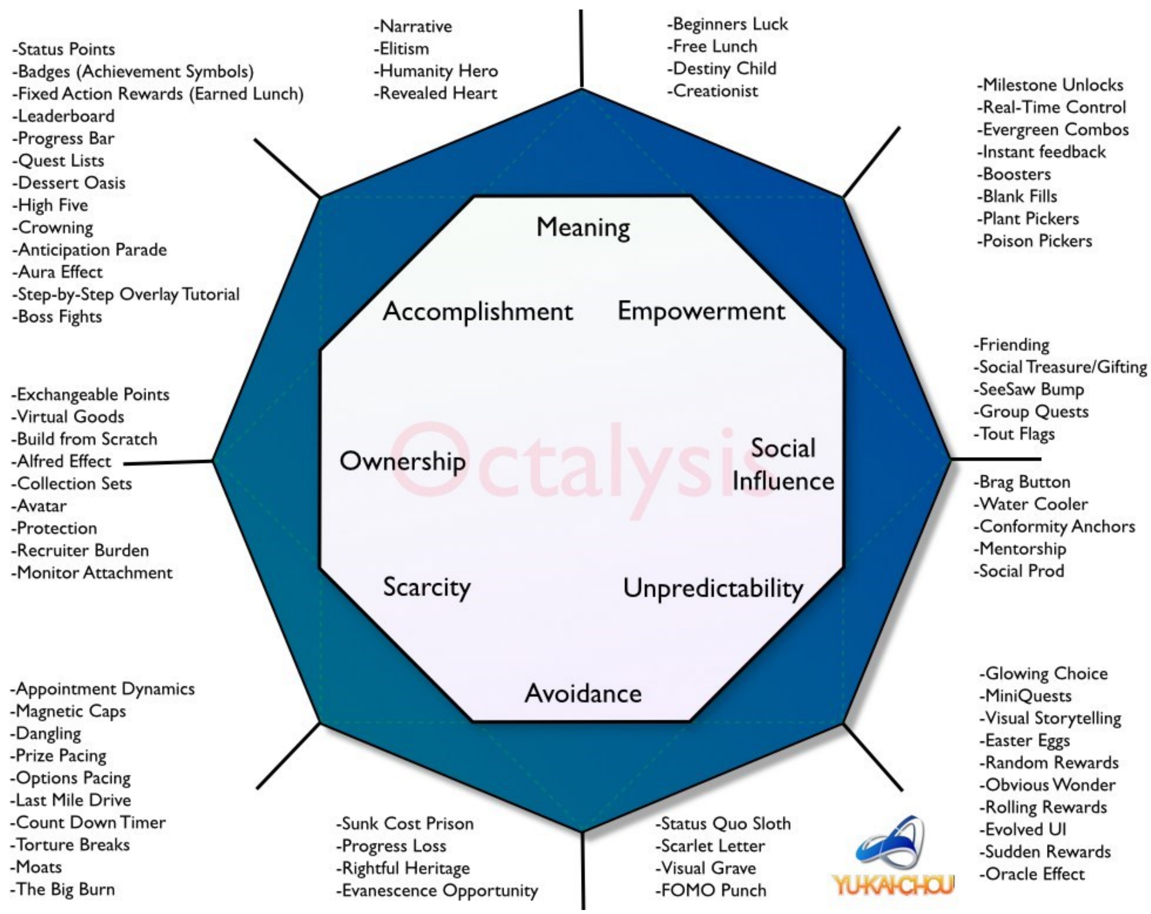
Appendices

- Appendix 1. Octalysis framework for actionable gamification to enhance engagement (Chou 2016)
- Appendix 2. Search terms used for concept explication and operationalization
- Appendix 3. Skata Architecture during Usability testing
- Appendix 4. Skata App/Website Page Log Dictionary
- Appendix 5. Skata Dashboard Data – Shell table with data descriptions
- Appendix 6. EEI Formulas applied to Skata data exhaust from April – August 2016
- Appendix 7. Consent form for Skata usability and follow-up interviews
- Appendix 8. Skata Usability test interview guide
- Appendix 9. Skata Follow-up interview guide
- Appendix 10. Table of Skata digital assets
- Appendix 11. Images of tested Skata and revised Skata
- Appendix 12. Dissemination of preliminary findings

Appendix 1. The Octalysis framework for actionable gamification to enhance engagement (Chou 2016)

Included from http://yukaichou.com/gamification-examples/octalysiscomplete-gamification-framework, accessed July 2017 and reprinted with permission from Yu-kai Chou.

This framework for engagement in gaming considers both the logical motivations for sustained use of a product as well as the more affect-oriented motivations. The outer text of the framework notes gaming features that can be used to improve upon each of the core motivation drivers to engage with a game. Entertainment is the fundamental driving motivation for game use.



Appendix 2. Search terms used for concept explication and operationalization

1. PubMed database

("2005/01/01"[Date - Publication] : "3000"[Date - Publication]) AND ((((((("telemedicine"[MeSH Terms] OR digital health[tiab] OR mhealth[tiab] OR mobile health[tiab] OR ehealth[tiab] OR telehealth[tiab] OR (mobile app[tiab] OR mobile apparatus[tiab] OR mobile appendages[tiab] OR mobile appendix[tiab] OR mobile application[tiab] OR mobile applications[tiab] OR mobile approach[tiab] OR mobile apps[tiab])) OR ("health"[MeSH Terms] OR ("health"[MeSH Terms] OR "health"[All Fields]) AND decision-support[All Fields])))) AND ((engagement[tw] OR engage[tw] OR engagement in care[tw] OR (user[All Fields] AND engagement[All Fields]) OR patient activation[tw] OR patient engagement[tw] OR customer engagement[tw])))))

2. Communication and Mass Media Complete (CMMC) database

((telemedicine OR digital health OR mhealth OR mobile health OR ehealth OR telehealth OR mobile app OR mobile application OR mobile applications OR mobile approach OR mobile apps) OR (health AND decision-support)) AND (engagement OR engage OR engagement in care OR activation OR patient engagement OR customer engagement))

3. Human Computer Interaction (HCI) Bibliography

(engage*) AND (medic* | nurs* | patient* | health | healthcare | doctor | doctors) AND ((mobil*|cell*|ubiquit*) OR (phone*|device*|comput*))

Appendix 3: Skata Architecture during Usability testing (Dec 2015 – April 2016)

Login

- Profile creation
- Two-part menu
  - Article
  - Main menu*

Re-login

- Two-part menu
  - Article
  - Main menu*

*Main menu

- Article
  - Each individual article with option to comment
- Contraception
  - Menstrual calendar
  - Fact or Myth Quiz
  - Contraceptive reminders
  - Contraceptive methods*
    - Each modern method
    - Find the right method for me
      - At the end of the recommendation it linked to each suggested method as well as find the nearest midwife
- Counseling
  - Ask a midwife list of topics
    - Detailed answers to questions on that topic, with option to rate answers
  - Find the nearest midwife
- Family planning
  - Immunization calendar
  - School calendar
  - School checklist (to plan school-related expenses)
  - Add child
- Developmental milestones
  - Per child, developmental milestone checklist for ages 0-5
- My Plan
  - Top section of the Plan linked to Contraceptive methods menu*
- To do
  - Daily checklist
  - Long-term checklist
- Settings
  - Add child
  - Modify profile

Appendix 4. Skata App/Website Page Log Dictionary

Short description of page and action tracked	Full description of page and action tracked
Main menu	User opens the main menu
1. Contraception menu	User views the main contraception section
a. Contraceptive information	User opens the menu listing all modern contraceptive methods
i. Find the right contraceptive for me	User answers a series of questions to determine the most effective contraceptive method for their fertility goals
b. Add contraceptive reminder	User adds the type of contraceptive s(he) uses and the date it was last used to calculate a reminder for when to replace/use the next contraceptive
c. Menstrual calendar	User views the menstrual calendar reminder feature
i. Add menstrual calendar data	User adds the dates of her last period to calculate when to expect her next period
2. Counseling menu	User views the main counseling section
a. Counseling categories	User browses the counseling frequently asked questions (FAQs) categories (e.g., Pregnancy)
i. Counseling list of questions within an FAQ category	User views the list of questions within a counseling FAQ category (e.g., What are the risks of pregnancy over age 35?)
1. Specific counseling information	User views one of the counseling FAQ answers in detail
a. Rating counseling information	User rates satisfaction with specific counseling FAQ answer provided
3. Family planning menu	User opens the family planning section
a. School calendar	User views the school calendar feature
b. Listing of children	User opens a feature that shows sub-menus for each child the user has added in the app
c. Education planning feature	User views the educational planning feature, where schooling levels are listed (e.g, Primary, Secondary) up to the planned education attainment level, per each child added in the app
i. Add child's planned education attainment level	User selects the level to which they plan to educate their child (e.g., though high school, through college, etc), per each child added in the app
ii. Check child's educational attainment	User marks levels of education their child has attained against planned education goals, within the educational planning feature, per each child added in the app
4. Article list	User views the list of articles
a. Specific article	User views a specific article

Short description of page and action tracked	Full description of page and action tracked
5. My Plan feature	User answers a series of questions to get individually tailored feedback about spacing & limiting children. Feedback includes a detailed timeline of the user/couple's life until approximately age 70
6. To do list	User types in a new to do list
a. Add task	User adds a new task to a to do list
i. Check task	User checks off a completed task on a to do list
ii. Delete task	User deletes a task from a to do list
7. Developmental milestone checklist	User marks developmental milestones child has achieved through age 5, per each child added in the app
8. User profile	User views his/her profile page

Appendix 5. Skata Dashboard Data – Shell table with data descriptions

User ID	Function	Method	Params1	Params2	Header	Raw Data	Created Date
Numeric unique identification number	Page accessed	Action of visiting page or inputting data	Number indicating detail to describe the function (e.g., for detailartikel the number corresponds to the specific article accessed)	If page is shared, method through which it was shared (e.g., Twitter, Facebook)	Indicates app or website version, and device used to access (e.g., iPhone or Android)	Synthesis of function, method, params 1 & 2 data generated per page visit	Date and time for page visit

Continued:

User ID	Usertype	Category	Location	Gender	Birth Year	Register Date
Numeric unique identification number	Login method: Facebook or email address	Life stage, determined through series of questions about birth year, marital status, parity and fertility goals	Free-type response of user's location	Male or female	Response to year of birth	Date and time user registered with Skata program

Appendix 6. EEI Formulas applied to Skata data exhaust from April – August 2016

Sub-scale	Formula	Calculation period, Data source	Final calculation	Meaning*
INCLUDED IN EEI APPLIED TO SKATA DATA EXHAUST				
Click Depth (CD_i)	$CD_{ij} = \frac{\text{\# Sessions where at least 2 web/app pages were viewed}}{\text{\# Sessions in j visit category}}$	Initial: j1 = visit 1 Interim j2 = visits 2-3 Final j3= visits 4+ n=3 Source: Data exhaust	$= \sum_{j=1}^{n}$ (Subscale_i /n) Each subscale ranges from 0-1	Behavioral engagement – Period of engagement, Depth of engagement
Duration (D_i)	$D_{ij} = \frac{\text{\# Sessions lasting at least 30 minutes}}{\text{\# Sessions in j visit category}}$			Behavioral engagement – Point through Period of engagement to Disengagement, Length of engagement, Depth of engagement
Loyalty (L_i)	$L_{ij} = 1 - \frac{1}{\text{Total visits from start of j visit category to end of j visit category}}$			Behavioral engagement – Point through Period of engagement to Disengagement, Length and frequency of engagement
Interaction (I_i)	$I_{ij} = \frac{\text{\# "Post" actions indicating user inputted data into app/website}}{\text{\# Actions user took in j visit category}}$			Behavioral engagement – Period of engagement, Feature-specific depth of engagement
Feature breadth (FB_i)	$FB_{ij} = \frac{\text{Average breath of features accessed in j visit category}}{\text{Features available to i user, based on life stage categorization in Skata}}$			Behavioral engagement – Period of engagement, "adequate" engagement with features conceptually linked to psychosocial mechanisms that predict behavior change
Recency (R_i)	$R_{ij} = \frac{1}{\text{Average \# hours between visits in j visit category}}$	j1 = visits 2-3 j2 = visits 4+ n=2 Source: Data exhaust		Behavioral engagement –Re-engagement & Dynamic nature of engagement

EEI SUBSCALES NOT APPLIED TO SKATA DATA EXHAUST				
Cognitive Engagement (CE)	$CE = \frac{\text{\# of DBCI downloads}}{\text{Estimated population of potential DBCI users}}$	Aggregate for study period Source: App hosting site (e.g., Google Play store, iOS App store)	= CE (constant per DBCI)	Cognitive engagement – Awareness of the DBCI
Feedback (F_i)	$F_i = \frac{\text{\# Questions respondent answers positively/as 'satisfied'}}{\text{\# Questions in survey}}$	Assessed at endline only Source: Close-ended user survey about satisfaction with DBCI	= F_i (calculated per individual i)	Emotional engagement – Satisfaction, usability, perceived quality and willingness to recommend
Feature-specific Use (FSU_i)**	$FSU_{ij} = \frac{\text{Average breath of z type of features accessed in j visit category}}{\text{Features available to i user}}$	Initial: j1 = e.g., visit 1 Interim j2 = e.g., visits 2-3 Final j3= e.g., visits 4+ n=3 z = specific type of feature (e.g., planning features) Source: Data exhaust	$= \sum_{j=1}^{n}$ (Subscale/n) If there are multiple FSU subscales, each is calculated as a separate subscale. Subscale ranges from 0-1	Behavioral engagement – Period of engagement, Feature-specific depth of engagement focused on "adequate" engagement with features conceptually linked to psychosocial mechanisms that predict behavior change

Note: In these formulas i=ith person, j=jth time period over 5-month study, and n (sum of the calculation period) = 3 for Di, Ci, Li, Ii, and FBi, and n=2 for Ri.
*The phases and facets of engagement represented by each subscale of the EEI.
**FSU was initially included in the Skata data exhaust analysis, with two FSU subscales for planning for the future and contraceptive decision-making. Inclusion of these subscales, however, did not improve the overall internal reliability (Chronbach's alpha) of the EEI and thus these FSU scales were dropped from the analysis.

CALCULATION OF THE EEI

EEI score$_i$ = Sum of $CD_i + D_i + L_i + I_i + FB_i + R_i + CE_i + F_i + FSU_i$.

To approximate a normal distribution, the EEI score is standardized to a z-score with mean 0 and standard deviation of 1.

Standardized EEI score = (EEIi – mean EEI)/std dev EEI.

Appendix 7. Consent form for Skata usability and follow-up interviews

Note: Also available upon request in Bahasa Indonesia

CONSENT FORM FOR USABILITY TEST
PI Name: Doug Storey **Study Title:** MyChoice: Reinvigorating the Family Planning Program in Indonesia **IRB No.:** 6181 **PI Version/Date:** V01/27 August 2015

Good morning/afternoon, I am _______________ from the Center for Health Research, University of Indonesia.

PURPOSE

We are conducting a research study for the Bill and Melinda Gates Foundation and the Government of Indonesia about use of mobile phone apps to find health information and use it to make family health decisions. The results of this study will be used to help improve the reproductive health services for families in this province. [Name], the cadre/midwife in this village, suggested that we invite you to participate in this study because you are a man/woman of reproductive age, 15-49 years old, a user [non-user] of family planning and are/have [life stage: newly married, one child, two or more children] and because you use a mobile phone that can access the internet and run mobile apps.

PROCEDURES

If you decide to participate in this study, we will introduce you to an app that has been created for women like you and, if you are willing and have a mobile phone that can run the app, we will help you load it on your phone, let you explore it for a few minutes, then ask you some questions about your reactions to it. A month from now, we will come back and talk to you about your reactions to the app after having it for a month. The information you provide may help to improve the quality of family planning programs and of the health services that you use.

Each interview will take 45-60 minutes.

Although there is a small risk that someone outside the study will learn about what we discuss, we will do all we can to prevent that from happening by keeping your contact information separate from what you say during our discussion. The information we collect will not be shared with anyone outside the study. It will be stored in a locked office and later destroyed when the study is complete.

Your participation in this study is voluntarily. You do not have to participate if it is inconvenient to you and you may refuse to answer any questions or stop the discussion at any time. We hope you can participate since your opinions and information are very important.

We will not pay you to participate in these interviews, but the mobile app is free and you may keep it on your phone and use it as you wish.

WHO TO CONTACT IF YOU HAVE QUESTIONS OR PROBLEMS

- Call the local investigator, RITA DAMAYANTI, Pusat Penelitian Kesehatan Universitas Indonesia, Kampus Baru UI Depok, Telp. 021-7270154 if you have questions or complaints about being in this study.

- If you have any questions about your rights as a research participant, or if you think you have not been treated fairly, you may contact Prof. Dr. Sudianto Kamso MD, Secretary of the Research Ethics Committee, University of Indonesia, Faculty of Public Health, Kampus Baru UI Depok, Telp. 021-7864975.

PERMISSION TO PROCEED

Are you willing to participate in the interview today? **Yes/No**

Are you willing to keep the mobile app on your phone for a month and participate in another interview at the end of that time? **Yes/No**

"A member of the study staff has explained the research study to me and I agree voluntarily to participate in the study."

________________________ ________________________ __________

Print name of Respondent Signature of Respondent Date

"I have read the consent form completely before the study participant and the study participant voluntarily agreed to participate in the study."

________________________ ________________________ __________

Print name of Person Obtaining Consent Signature of Person Obtaining Date Consent

Appendix 8. Skata Usability test interview guide

Available upon request in Bahasa Indonesia

Initial Interview:
Mobile literacy, Current App habits & Introduction to the SKATA Mobile Phone App

Current app habits
What apps, or programs that you download to your phone, do you currently have on your phone?

- Did you put these apps on your phone?
- Are you the only one who uses these apps? If not, who else uses these apps, or this phone?
- Which app do you use most often? Why do you enjoy using that app in particular?

Mobile Literacy
Please indicate your ability to carry out the following functions on your mobile phone without assistance:

	FUNCTION	YES	Yes, but with help	NO	Don't Know
A	Download a program (app) to your phone				
B	Open an app on your phone				
C	Open an article using a link within a phone app				
D	Comment on an article or post within a phone app				
E	Share an article or image from a phone app (i.e., share on facebook, twitter)				
F	Play games stored on the phone				
G	Navigate internet from your phone (ie. google, facebook)				
H	Use internet to instant message (i.e. whatsapp, skype)				
I	Use GPS to get directions using phone (i.e, map)				
J	Save a new contact				
K	Play audio or video on phone				
L	Adjust volume on phone				
M	Check the phone calendar				
N	Access phone settings				
O	Manage battery life				
P	Access wi-fi network				

Interviewer should download app to the user's phone and open it. Allow the participant 10 minutes for initial app exploration (self-guided, uninterrupted). NOTE: Interviewer should note any instances in which she notices the participant seems confused or unable to understand how to navigate a section of the app.

What is your overall impression of this app?

- Who do you think this app is for? (Probe: Is it for someone like you? Why or why not?)
- Does this app seem interesting? What makes you say that?

- Does this app seem practical for you to use? What makes you say that? Are there any places or situations in which you would avoid using this app? What makes you say that?

Tell me what you did during your first 10 minutes with the app. (Have participant walk through each step.)

- Registration: Why did you choose to/ not to register yourself in this app? After you explored more of the app, would you have made a different decision about registering?
- First menu item selected:
    - What made you want to look at this section of the app first? What did you think about this section?
    - How understandable was the information in this section?
    - Was the information in this section new to you, or something you did not know earlier? If yes, what was new?
    - Now that you looked at the section, would you ever plan to return to it again? Why or why not?
- Additional menu items selected (continue for as many sections of app that were explored):
    - What made you want to look at this section of the app next? What did you think about this section?
    - How understandable was the information in this section?
    - Was the information in this section new to you, or something you did not know earlier? If yes, what was new?
    - Now that you looked at the section, would you ever plan to return to it again? Why or why not?

If not discussed, show participant Counseling section of app. Show list of questions, and answer to at least 2 questions.

- What is your overall impression of this section of the app?
- What do you like about this section? What makes you say that?
- What do you dislike about section? What makes you say that?
- Is there any other topic you wish would have been included in this section? Why do you want this topic included?
- In the next month, do you think you will return to this section of the app? Why or why not?
- Do you trust the information that is provided here? What makes you say that?

If not discussed, show participant Myth or Fact quiz section of app. Show at least 2 questions and answers.

- What is your overall impression of this section of the app?
- What do you like about this section? What makes you say that?
- What do you dislike about section? What makes you say that?
- In the next month, do you think you will return to this section of the app? Why or why not?
- Do you trust the information that is provided here? What makes you say that?

If not discussed, show participant “What contraception suits me” section of app. Go through questions to get to a recommendation of contraceptive method.

- What is your overall impression of this section of the app?
- What do you like about this section? What makes you say that?
- What do you dislike about section? What makes you say that?

- In the next month, do you think you will return to this section of the app? Why or why not?
- Do you trust the information that is provided here? What makes you say that?

Now that you have spent more time looking at this app, have your impressions of it changed? In what way?
- What parts of this app are easy to use? What makes you say that?
- What parts of this app are difficult to use? What makes you say that?
- Did you learn to use any new features of your phone while using this app? Which ones?
- What else should an app about planning for children and your family include? Why would this addition be important?
- Could this app affect the way you get information about FP? In what way?
- How comfortable are you with sharing your activity in this app with others (e.g., sharing quiz results or articles from app on social media)? What makes you say that?
- In the next month, do you think you will use this app any further? What makes you say that? (Probe: what features of the app peak your interest in using this app again?)

Anything else you would like to add or ask us?
Thank you.

Appendix 9. Skata Follow-up interview guide

Available upon request in Bahasa Indonesia

Follow-Up Interview:
User Experience with SKATA after One Month

(Starting language to greet participant, explain interview purpose and procedures, as well as ground rules.)

In the past month, since our previous meeting, did you use the SKATA app again? About how often did you use it?

- What is your overall impression of the app now? What makes you say that?
- Is this app interesting? What makes you say that?
- Is this app practical for you to use? What makes you say that?
- What features of the app did you use? How did you use this feature? (Probe: location, time of day, length of use, frequency of use) If used a feature multiple times, what made you want to use that feature more than once?
- What features of this app did you most enjoy using? Why did you enjoy that feature?
- What features of this app did you dislike using? Why did you dislike that feature?

I would like to ask you more about the situations in which you used the app.

- Did you use the app alone, or with other people?
- In what situations did you usually use the app? (Probe: leisure time at home, when waiting/in line outside home, at a specific time and place, before FP clinic visit, when the app prompted you to revisit it, etc)
- Were there any places or situations in which you would avoid using this app? (Probe: at work/school, when in company of strangers, when in company of husband, etc) Why did you avoid using it in those situations?
- Are there certain features of the app you did not feel comfortable using in public settings? Which features? What made you uncomfortable about these?
- Are there certain features of the app you did not feel comfortable using when in your home? Which features? What made you uncomfortable about these?

I would like to ask you more about how people around you reacted to your use of the app.

- Did your husband know about this app on your phone? If no, would you have been comfortable telling your husband that you have this app on your phone?
    - How did he feel about your having this app? Or, how do you think he would feel about your having this app?
    - Did he encourage you to use this app? Why or why not?
    - Did you talk to your husband about anything you read or saw in this app? What did you discuss? How did he react to your mentioning this information?

- Who else lives with you in your household? (E.g., mother-in-law, etc) Did these people know about this app on your phone? If no, would you have been comfortable telling them that you have this app on your phone?
    - How did this person feel about your having this app? Or, how do you think he/she would feel about your having this app?

    - Did this person encourage you to use this app? Why or why not?
    - Did you talk to this person about anything you read or saw in this app? What did you discuss? How did he/she react to your mentioning this information?

- Who do you talk to regularly outside of your household? (E.g., neighbors, friends, extended relatives, community group members, etc) Did these people know about this app on your phone? If no, would you have been comfortable telling them that you have this app on your phone?
    - How did this person feel about your having this app? Or, how do you think he/she would feel about your having this app?
    - Did this person encourage you to use this app? Why or why not?
    - Did you talk to this person about anything you read or saw in this app? What did you discuss? How did he/she react to your mentioning this information?

- How active are you on social media (such as Facebook, Instagram and Twitter)?
    - Who are you connected to via social media (e.g., friends, family members, co-workers, casual acquaintances)?
    - Did you share any of the content from this app with your social media contacts? What information did you share? If no, would you have been comfortable sharing information from this app (e.g., life stage, articles) with your social media contacts? Why or why not?
    - Did your social media contacts encourage you to use this app? Why or why not?
    - Did you have conversations on social media about anything you read or saw in this app? What did you discuss? How did your social media contacts react to your mentioning this information?

- Did you talk with your FP provider or local health worker anytime in this month? Did she know about this app on your phone? If no, would you have been comfortable telling her that you have this app on your phone?
    - How did the health worker feel about your having this app? Or, how do you think she would feel about your having this app?
    - Did the health worker encourage you to use this app? Why or why not?
    - Did you talk to the health worker about anything you read or saw in this app? What did you discuss? How did she react to your mentioning this information?

We are nearly finished with our conversation. I would like to end by understanding how you see this app fitting into your life in the future.

- Do you plan to continue to use this app in the next month? Why or why not?
- Did this app make you reconsider your family planning method? How so?
- What are some reasons that would make you consider changing your family planning method? If one of those events happened, do you think you would refer to this app? Why or why not? When else would you use this app in the future? Why then?
- Do you plan to recommend this app to other people you know? Who would you recommend this app to? Why do you think this app would be useful to that person?

Anything else you would like to add or ask us?
Thank you.

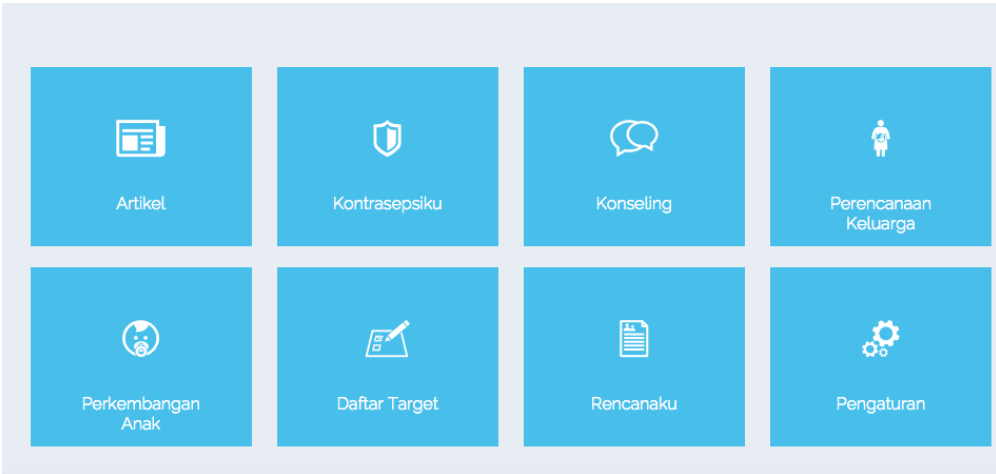
Appendix 10. Table of Skata digital assets

Skata Digital asset	Web Address
Skata app	Google Play Store: https://play.google.com/store/apps/details?id=mobi.mobileforce.skata&hl=en iOS store: https://itunes.apple.com/ca/app/skata/id1056608584?mt=8
Skata website	http://skata.info
Skata Facebook page	https://www.facebook.com/SKATAID
Skata Instagram page	https://www.instagram.com/skata_id/
Skata Twitter page	https://twitter.com/skata_id
Skata Google Plus page	https://plus.google.com/111703775062687985608/posts
Skata YouTube channel	https://www.youtube.com/channel/UCIhWPv79a7LDyNNjXHAZWFw

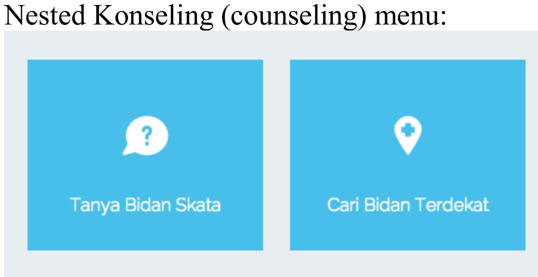
Appendix 11. Images of tested Skata and revised Skata

Skata as tested, version 2: circa April 2016

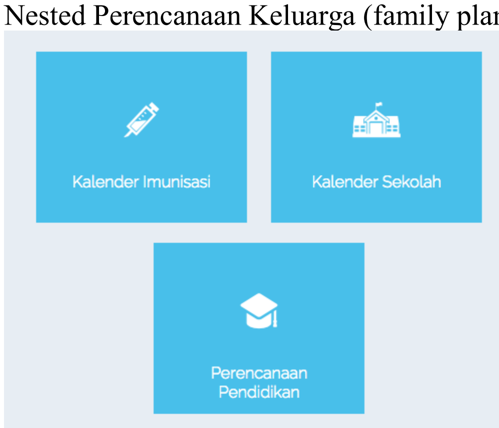
Main menu:



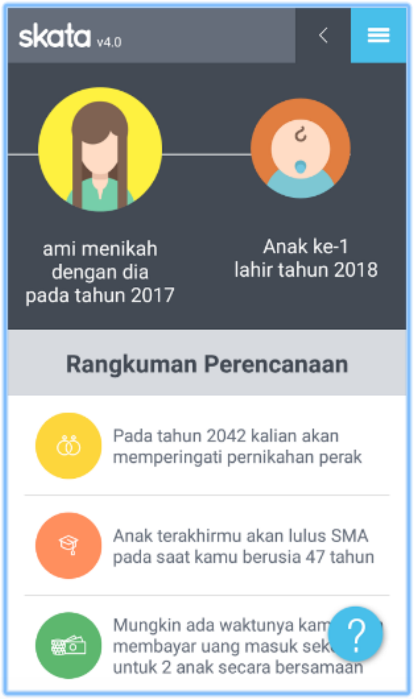
Nested Konseling (counseling) menu:



Nested Perencanaan Keluarga (family planning) menu:

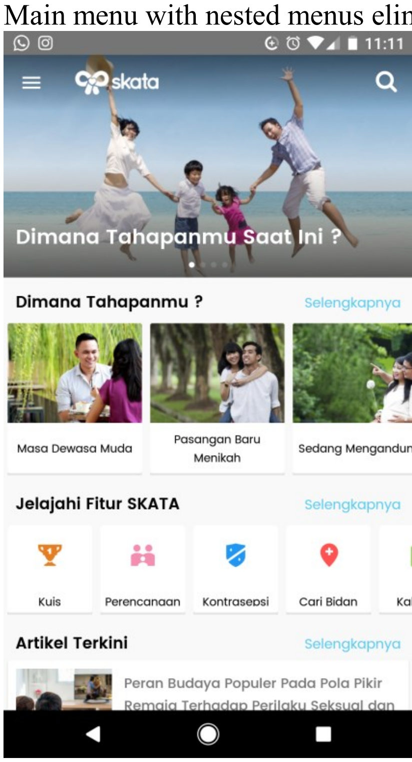


My Plan feature:

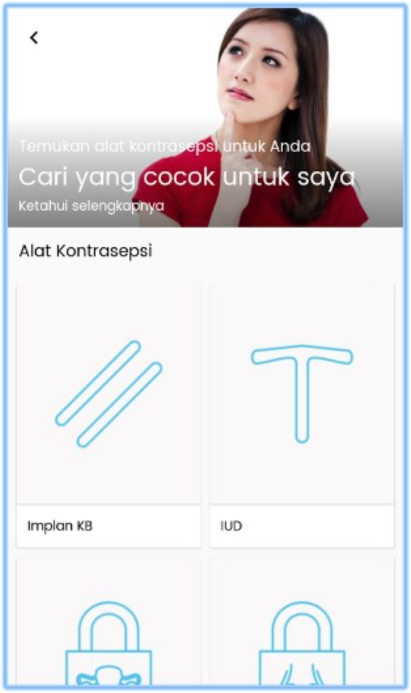


Skata as revised after usability testing, version 4: circa February 2018

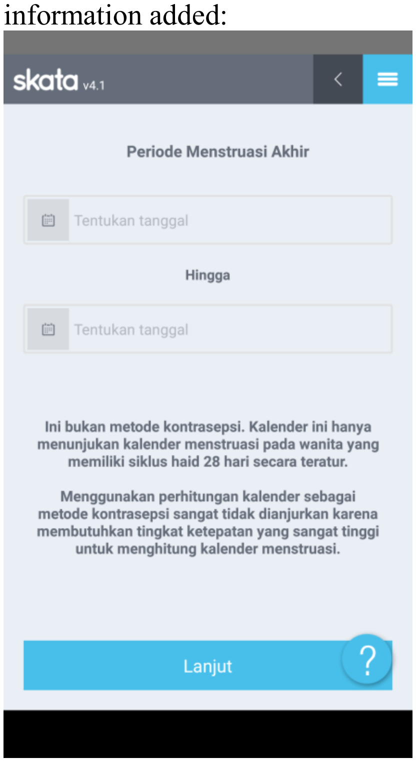
Main menu with nested menus eliminated:



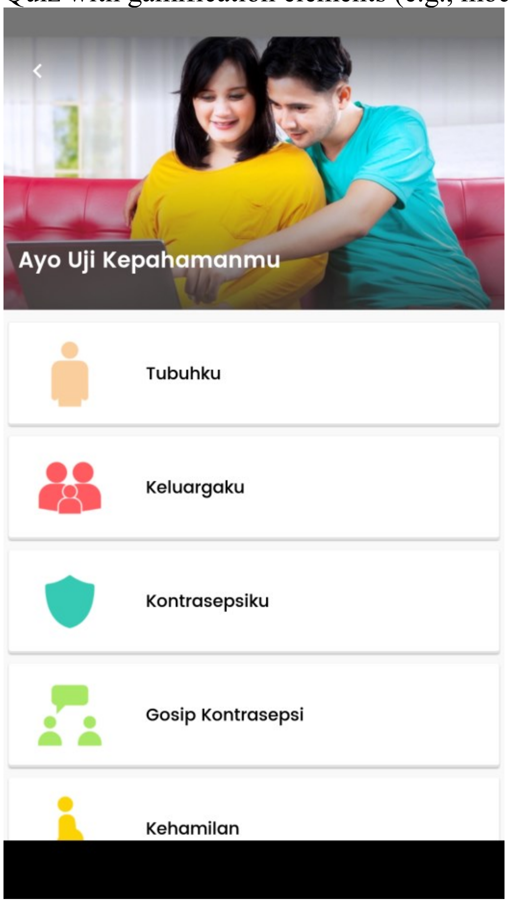
Enhanced aesthetic appearance, e.g., contraceptive method menu:



Contextualizing popular features, e.g., menstrual calendar with Standard Days Method information added:



Quiz with gamification elements (e.g., modules):



Appendix 12. Dissemination of preliminary findings

International Social and Behavior Change Communication Summit, February 2016. Rajan R. Poster "Mobile media consumption to inform family planning promotion in Indonesia." Addis Ababa, Ethiopia.

Johns Hopkins Global Health Day, April 2016. Rajan R. Poster "Right Time. Right Method. MyChoice. Reinvigorating Family Planning in Indonesia." Baltimore, MD.

Johns Hopkins Digital Health Day, December 2016. Rajan R. Presentation "Influences on Engagement." Baltimore, MD.

Johns Hopkins Center for Qualitative Studies in Health and Medicine, March 2017. Rajan R. Presentation "Digital Engagement: Understanding patterns of sustained use of a mobile application for family planning in Indonesia." Baltimore, MD.

Johns Hopkins Health Communication Programs II course, April 2017. Rajan R. Presentation "Digital Engagement & Sustainability of a Digital Health Strategy." Baltimore, MD.

Global Digital Health Forum, December 2017. Rajan R. Panel presentation. "Digital Engagement: It's a process, not just an outcome – Findings from Testing the SKATA mobile app for family planning in Indonesia." Washington, DC.

Global Digital Health Forum, December 2017. Rajan R. Poster "Influences on engagement in digital health interventions for behavior change: A review of the literature." Washington, DC.

***Upcoming:* International Social and Behavior Change Communication Summit, April 2018.** Rajan R. Presentation "An innovative approach to digital health measurement: Focusing on users NOT motivated to change." Nusa Dua, Bali, Indonesia.

***Upcoming:* International Social and Behavior Change Communication Summit, April 2018.** Rajan R, Pandan Sari, D. Presentation "A novel approach in usability testing to refine ICT strategy." Nusa Dua, Bali, Indonesia.

***Upcoming:* International Social and Behavior Change Communication Summit, April 2018.** Leslie L, Rajan R. Skills building workshop "Excel-ing at Data for Decision-Making." Nusa Dua, Bali, Indonesia.

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Wilson, M. G., Sweet, C. M. C., Edge, M. D., Madero, E. N., McGuire, M., Pilsmaker, M., ... & Kirschner, S. (2017). Evaluation of a Digital Behavioral Counseling Program for Reducing Risk Factors for Chronic Disease in a Workforce. Journal of occupational and environmental medicine, 59(8), e150.

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Ziebland S., Powell J., Briggs P., Jenkinson C., Wyke S., Sillence E., … & Farmer, A. (2016). Examining the role of patients' experiences as a resource for choice and decision-making in health care: a creative, inter-disciplinary mixed-method study in digital health. Programme Grants and Applied Research, 4(17): 51-61.

Curriculum Vitae

RADHA RAJAN, MHS, DrPH

Department of Health, Behavior & Society, Johns Hopkins School of Public Health
rrajan1@jhu.edu
Born: Lapeer, MI, USA - Nov. 15, 1980

RESEARCH PROFILE

Self-motivated, insightful and diligent researcher interested in digital health for social and behavior change communication. Strong background in qualitative and quantitative methods and a commitment to investigating practice-oriented research questions tied to programmatic refinement. Experienced in global and domestic public health.

EDUCATION

JOHNS HOPKINS BLOOMBERG SCHOOL OF PUBLIC HEALTH **May 2018**
DrPH, Baltimore, MD.
Department of Health, Behavior and Society

JOHNS HOPKINS BLOOMBERG SCHOOL OF PUBLIC HEALTH **Dec 2007**
Master of Health Science (Honors). Certificate in Health Communication. Baltimore, MD.
Department of International Health, Social and Behavioral Interventions

THE GEORGE WASHINGTON UNIVERSITY **May 2002**
Bachelor of Arts (Honors). Washington, DC.
Major: Anthropology. Minor: French

THESIS RESEARCH

***MYCHOICE* PROGRAM/SKATA APPLICATION** **Jakarta, Indonesia**
Exploring 'engagement' with digital interventions for behavior change **8/15 – 5/18**

- Advised local program implementation and app development teams on mobile app design and development of a dashboard for viewing real-time data on app users.
- Oversaw 65 structured interviews conducted in Bahasa Indonesia across three program sites. Interviews explored feasibility, acceptability and impact of the *Skata* mobile application, as well as technical features, interpersonal relationships and communication norms about family planning information seeking and decision-making that either facilitate or inhibit 'engagement,' or sustained use of the app.
- Conducted analyses of 20,000+ respondent baseline household survey data to identify extent of mobile phone and app use, and explore knowledge, attitudes and behaviors associated with use of family planning methods.
- Thesis includes a concept explication of engagement and proposal of the Extended Engagement Index to measure engagement in digital tools for health behavior change, qualitative analysis to understand how motivation shaped engagement in the *Skata* mobile application, an exploratory factor analysis to identify types of engagement based on *Skata* usage data, and regression analyses to identify predictors of engagement.

WORK HISTORY

JHPIEGO MATERNAL AND CHILD SURVIVAL PROGRAM **Baltimore, MD**
Research Consultant **12/16 – 5/17**

- Produced report about lessons learned from implementation of the Mobile Alliance for Maternal Action (MAMA) country programs in Bangladesh, South Africa, India and Nigeria. Executive summary shared at the ICT4D 2017 Conference in Hyderabad, India and December 2017 Global Digital Health Forum in Washington, DC.
- Collaborated with and incorporated feedback from staff from USAID, Johnson & Johnson, BabyCenter, Praekelt Foundation and the four country programs that implemented MAMA.

GEORGE WASHINGTON MILKEN INST. SCHOOL OF PUB HLTH **Washington, DC**
Adjunct faculty, Global Health Communication Strategies and Skills Course **8/16 – 12/16**

- Develop curricula and teach MPH-level practice-oriented seminar on global health communication programs.
- Course focuses on skills development, from strategic planning to development of research protocols, message development and evaluation of programs rooted in social and behavior change theory.

FRAMED, INTERACTIVE THEORY-DRIVEN TEXT PROGRAM **Baltimore, MD**
Research Lead **6/14 – 5/15**

- Developed a text message-based intervention for healthy eating and physical activity promotion, informed by Stages of Change behavioral theory and research on framing messages for present vs. future and gain vs. loss orientations. Worked with the eMocha platform team to develop and test the technology for the intervention.
- Led a team of 12 undergraduate and Masters level students in conducting a pilot study of the Framed, Interactive Theory-Driven Text (FITT) program. Included IRB protocol development, quantitative and qualitative instrument development, and two rounds of data collection from 89 participants across 4 churches in Baltimore City.

STILETTO Research Study **Baltimore, MD**
Data Collector, Quality Assurance **4/13 – 10/14**

- Developed memos recording observational data on risk environments for drug use and transactional sex in exotic dance clubs in Baltimore City and County.
- Conducted survey interviews with exotic dancers to gather socioeconomic data and perceived norms about risk environments in their workplaces, as well as biological samples for STD testing.
- Monitored receipt of data to ensure complete reporting from each data collector at each field visit.

MAMA APONJON FORMATIVE RESEARCH **Baltimore, MD for Bangladesh**
Research Lead **5/13 – 8/14**

- Analyzed formative research data from the Mobile Alliance for Maternal Action (MAMA) program in Bangladesh.
- Lead author of the MAMA Aponjon Formative Research Report, which was published in May 2014 on the MAMA Global website. Included supervision of a graphic designer to produce a high-quality product.
- Promoted the findings through several presentations and an online course accessed by over 400 participants.

INTERNATIONAL CENTER FOR RESEARCH ON WOMEN **Dakar, Senegal**
Qualitative Research Consultant **3/11 – 5/12**

- Designed and spearheaded implementation of a research plan to explore the potential added value of addressing gender equity through Tostan's non-formal community empowerment educational program.
- Secured expedited IRB approval of research plan, consent materials and interview instruments.
- Led a workshop with Tostan staff, using participatory learning approaches to document the history, challenges and successes of implementing the Nike Foundation CEP+ program in 50 villages across Senegal.
- Directed a team of six field staff, including provision of training in qualitative methods, facilitation, note-taking, and production of high-quality translated transcripts. Conducted majority of work with field staff in French.
- Analyzed qualitative data from a total of 30 interviews and focus group discussions to develop a report documenting attitudinal and behavioral impacts of Tostan's curriculum, particularly with the inclusion of modules specifically discussing gender equity.

INSTITUTE FOR REPRODUCTIVE HEALTH **Washington, DC**
Qualitative Research Consultant **9/10 – 12/10**

- Analyzed nine French-language focus group transcripts using Atlas.ti.
- Identified shifts in perceived gender norms through inductive coding and data analysis, to measure impact of a sexual and reproductive health curriculum on the lives of very young adolescents in Rwanda.
- Drafted report for the Georgetown Institute of Reproductive Health.

PORTER NOVELLI PUBLIC SERVICES **Washington, DC**
Research Supervisor **3/08 – 3/11**

- Managed research team of up to four staff and facilitated qualitative sessions to document target audience mindset and perceived barriers to accessing information and adopting healthier behaviors for clients such as the CDC, U.S. Department of Agriculture and the Rhode Island Department of Public Health.
- Prepared budgets, oversaw vendor procurement, drafted research instruments, synthesized findings via written reports and delivered client presentations with evidence-based recommendations for program development and refinement.
- Collaborated with over 20 offices at the CDC, as well as a number of other government clients and internal staff to develop tracking indicators to field via Porter Novelli's five annual, longitudinal, nationally representative *Styles* surveys. Facilitated publication of numerous journal articles presenting *Styles* data.
- Conducted analyses using SPSS on datasets with over 10,000+ respondents, identifying insights into target audiences and communication strategy. Made oral and written presentations of findings to clients.
- Contributed to business development efforts; assisted in winning $280K worth of new business for the company in the first quarter of 2011.

ACADEMY FOR EDUCATIONAL DEVELOPMENT **Addis Ababa, Ethiopia**
Research Consultant, Health Communication Partnership Project **9/06 – 3/08**

- Designed research methodology and supervised implementation of a qualitative impact evaluation of two youth-focused HIV prevention programs in Ethiopia.
- Analyzed data from 72 in-depth interviews among HIV prevention program participants using N*Vivo.
- Authored two evaluation reports, each with guidance on program improvement to ensure the greatest impact.
- Presented baseline evaluation findings to USAID-funded partners working on HIV prevention in Ethiopia.

JOHNS HOPKINS CTR FOR HEALTH COMM. PROGRAMS **Baltimore, MD**
Program Associate, VOICES for a Malaria-Free Future **1/08 – 3/08**

- Conducted a mid-term evaluation of the Gates-funded Voices for a Malaria-Free Future project, with focus on program's influence of malaria in traditional print, broadcast and online news media.
- Back-stopped for Ghana program office, assisting them in incorporating as a local NGO.

JOHNS HOPKINS BLOOMBERG SCHOOL OF PUBLIC HEALTH **Baltimore, MD**
Process Evaluation Advisor, Baltimore Healthy Stores Project **9/05 – 5/06**

- Monitored implementation of Baltimore Healthy Stores interventions to refine program strategy and identify factors for success in promoting healthier food and beverage choices to community residents shopping in the city's corner stores.
- Co-authored process evaluation article, published in the Sept. 2010 issue of Health Promotion Practice.

NATIONAL ASSOC. OF COUNTY AND CITY HEALTH OFFICIALS **Washington, DC**
Program Associate, Community Health and Public Health Infrastructure **9/02 – 5/05**

- Hosted trainings and provided technical assistance to over 3,000 local health departments across the U.S on topics including: primary care, rural health, chronic disease, and strategic planning.
- Conducted interviews with health directors across the U.S. to write a case study publication on local public health agency and school board collaboration to address child nutrition and physical activity.
- Documented community mobilization and strategic planning processes at seven local public health departments implementing the Mobilizing for Action through Planning and Partnerships program.
- Developed conference abstracts, quarterly updates to project funders and grant proposal applications.

VOLUNTEER EXPERIENCE

HIPS Mobile Outreach and National 24-hour Hotline **Washington, DC**
Volunteer **9/11 – 3/14**

- Delivered non-judgmental harm reduction counseling and services through overnight outreach once a month, with particular focus on promoting the health and human rights of DC-area people involved in sex work and/or drug use.
- Counseled callers to a national hotline using harm reduction principles, referring them to services where possible and providing a compassionate ear to those in need. Calls ranged in topics, and often touched upon sex work, safer sex practices, relationship struggles, and housing issues.

Journal Manuscript Peer-Reviewer **2/16 – present**

- Peer-reviewed manuscripts and research protocols for Journal of Behavioral Medicine, British Medical Journal (BMJ) and Journal of Medical Internet Research (JMIR).

SKILLS

LANGUAGES: French (fluent reading, intermediate speaking and writing), Bahasa Indonesia (beginner speaking)

SOFTWARE: STATA, SPSS, N*Vivo, Atlas.ti, MPlus, UCINet, NetDraw, Simmons/Experian research database, Microsoft Office program suite

PUBLICATIONS

Rajan R, Liu A, Ollis S. May 2018. *Lessons from Country Programs Implementing the Mobile Alliance for Maternal Action (MAMA) Program in Bangladesh, South Africa, India and Nigeria, 2010 – 2016.* Maternal and Child Survival Program: Washington, DC, USA.

Cohen A, Perozich A, Rajan R, Persky S, Parisi J, Bowie J, Fahle J, Cho J, Krishnan A, Cohen Z, Ezike A, Schulte C, Taylor J, Storey D, Ahmed RS, Cheskin LJ. Jan/Mar 2017. "Framed Interactive Theory-Driven Texting: Effects of message framing on health behavior change for weight loss." *Family and Community Health.* 40(1): 43-51.

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Pande RP, Ogwang S, Karuga R, Rajan R, Kes A, Odihambo FO, Laserson K, Schaffer K. May 2015. "Continuing with...'a heavy heart' – consequences of maternal death in rural Kenya." *Reproductive Health.* 12 (Supplement 1): S2.

Rajan R, Raihan A, Alam M, Agarwal S, Ahsan A, Bashir R, Lefevre A, Kennedy C, and Labrique AB. December 2013. *MAMA 'Aponjon' Formative Research Report.* Johns Hopkins University Global mHealth Initiative: Baltimore, MD, USA.

Gittelsohn J, Suratkar S, Song H-J, Sacher S, Rajan R, Rasooly IR, Bednarek E, Sharma S and Anliker JA. Sepetember 2010. "Process Evaluation of Baltimore Healthy Stores: A Pilot Health

Intervention Program with Supermarkets and Corner Stores in Baltimore City." Health Promotion Practice. 11(5): 723-732.

Deutsch H, Joh-Elligers J, and Rajan R. September 2005. "Next Steps for MAPP." Journal of Public Health Management and Practice. 11(5): 474-475.

Rajan R and Green E. June 2005. "Building Healthier Schools: Local Collaborations to Promote Nutrition and Physical Activity." NACCHO.

CONFERENCE PRESENTATIONS/POSTERS

International Social and Behavior Change Communication Summit, April 2018. Rajan R. Panel presentation. "An Innovative Approach to Digital Health Measurement: Focusing on Users NOT Motivated to Change."

International Social and Behavior Change Communication Summit, April 2018. Rajan R, Pandan-Sari, D. Panel presentation. "A Novel Approach to Usability Testing to Refine ICT Strategy."

International Social and Behavior Change Communication Summit, April 2018. Leslie, L, Rajan R. Skills building session. "Excel-ing at Data for Decision-Making."

Global Digital Health Forum, December 2017. Rajan R. Panel presentation. "Digital Engagement: It's a process, not just an outcome – Findings from Testing the SKATA mobile app for family planning in Indonesia."

Global Digital Health Forum, December 2017. Rajan R. Poster "Influences on engagement in digital health interventions for behavior change: A review of the literature."

International Social and Behavior Change Communication Summit, February 2016. Rajan R. Poster "Mobile media consumption to inform family planning promotion in Indonesia."

TechChange online course: Early considerations for M&E and research for MNCH mobile messaging projects, August 2014. Rajan R. Presentation "Formative evaluation – Results of the MAMA Aponjon formative research study." *700+ participants, worldwide, have accessed the online course recording.*

mHealth Working Group, June 2014. Rajan R. Presentation "MAMA Aponjon formative research and evaluation design."

Global mHealth Initiative, May 2014. Rajan R. Presentation "MAMA Aponjon formative research findings."

National Conference on Health Communication, Marketing and Media, Centers for Disease Control, August 2010. Funderburk F, Salerno L, Rajan R, Burns A, Koepke C, Kickham T. Presentation "Maximizing message dissemination among low-income Medicare beneficiaries - Targeting and segmenting: Keys to successful social marketing campaigns."

American Public Health Association Conference, October 2008. Rajan R, Nanda G, Franca-Koh AC, Orleans-Lindsay, E. Presentation "Impact evaluation, quantitative and qualitative findings of the youth action kit and sports for life programs in Ethiopia 2006-2007."

AWARDS

Johns Hopkins School of Public Health Doctoral Student Practice Award for Excellence in International Public Health Practice. 2018. Selected in school-wide competition for recognition of contribution to international public health practice-oriented research with the Skata MyChoice program.

Health, Behavior & Society Student Organization Teaching Assistant Award. 2016-2017. Selected by peers in the Health, Behavior & Society department at Johns Hopkins School of Public Health for excellence as teaching assistant for the Health Communication Programs I&II courses.

Distinguished Doctoral Research Award. 2016-2017. $1,500 awarded to support travel and fees for research dissemination at relevant conferences. Department of Health, Behavior and Society, Johns Hopkins School of Public Health.

Sommer Scholarship for Health, Behavior and Society. 2016-2017. $10,000 awarded to support tuition fees. Department of Health, Behavior and Society, Johns Hopkins School of Public Health.

Dissertation Enhancement Award. 2015-2016. $1,500 awarded to support transcription and translation of interviews for thesis research. Center for Qualitative Studies in Health and Medicine, Johns Hopkins School of Public Health.

Distinguished Doctoral Research Award. 2015-2016. $2,000 awarded to support thesis research. Department of Health, Behavior and Society, Johns Hopkins School of Public Health.

Global Health Established Field Placement Award. 2015-2016. $3,500 awarded to support travel and lodging for thesis research in Indonesia. Center for Global Health, Johns Hopkins School of Public Health.

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